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# Technological Innovation, AI, and ESG: A Comprehensive Study on the Firm Life Cycle in Chinese A-Share Firms

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*Amidst the ongoing artificial intelligence (AI) technology revolution, businesses are increasingly embracing AI and environmental social and governance principles. This integration leads to sustainable business operations, improved efficiency, and enduring value creation to address global challenges. Therefore, this study explores that how AI technology enhance firm ESG performance through firm life cycle stages. By analyzing a sample of Chinese A-share listed firms from 2010-2020, the study primary findings reveal that AI technology significantly improves firm ESG performance, emphasizing the importance of technological advancements in ESG initiatives. Furthermore, the study reveals that the impact of AI on ESG is more pronounced during the growth and mature stages of the firm cycle compared to the introduction, decline and shakeout stages. Additionally, the study investigates this impact through two channels: AI enhances green innovation and firm performance, which in turn enhance ESG performance. Moreover, heterogeneity analysis highlighting a more pronounced effect in non-SOEs compared to SOEs, and in low bank concentration and robustness analysis through 2SLS and PSM.*

Keywords: *Artificial Intelligence; ESG; Environmental; Social; Governance; Firm Life Cycle; Green Innovation.*

## Introduction

Digital technologies such as artificial intelligence (AI) technology, big data and blockchain stand as pillars of civilization's evolution, offering boundless potential for societal progress (Li *et al.*, 2024b). The swift proliferation of these novel technologies has underscored the significance of AI technology as a critical driver for both economic expansion and environmentally sustainable development (Chen *et al*., 2023). However, AI is revolutionizing the world by unlocking the limitless potential and transforming various aspects of life (Yang *et al.*, 2024). For instance, it has revolutionized education, enabling greater customization and accessibility (Zhang & Aslan, 2021). Additionally, AI enhances corporate management, leading to improved decision-making and efficiency (Hussain *et al.*, 2024; Yang *et al.*, 2024). The growing dependence of AI underscores its increasing significance and profound impact on future developments within firm.

Existing studies have discovered that AI technology within the operational milieu of firms not only extends cost reduction and productivity (Czarnitzki *et al*., 2023), but it also leads to improvements across various fronts. These include upgrading operational efficiency (Brynjolfsson *et al.*, 2018), enhancing financial and innovative performance (Bahoo *et al.*, 2023; Bosse *et al.*, 2023), and boosting overall economic performance (Aghion *et al.*, 2018). Furthermore, AI also positively influences non-economic aspects like corporate social responsibility, the efficiency of human resource management and green development initiatives (Cardinali & De Giovanni, 2022; Chen *et al*., 2023). These studies shed light on how firms navigate the digital age, leading to substantial shifts in their operational framework and financial outcomes. Nevertheless, amidst this transformation, firms must confront various challenges concerning their sustainable performance, particularly when viewed through the lens of environmental, social and governance (ESG) considerations. These challenges encompass deficiencies in environmental consciousness, inadequate focus on employee rights and working conditions and deficiencies in product safety assurance systems (N. Wang *et al.*, 2022).

In recent years, there has been a surge among firms, governments and academia to align ESG goals with financial success (Alareeni & Hamdan, 2020). Simultaneously, the AI technology has reshaped the operational landscape of the contemporary digital economy. This transformation has rippled through management practices, innovation strategies, productivity levels and overall performance metrics (Bahoo *et al*., 2023; Bosse *et al.*, 2023; Czarnitzki *et al*., 2023). Given the significance of prior research and the influence of AI on various firm-level aspects, this study aims to examine the impact of AI on ESG performance within the context of firm life cycle stages (FLCS). To gain a deeper theoretical insight into this nexus it is imperative to consider several key attributes. The FLC theory posits that firms progress through identifiable and predictable phases, from introduction to decline. Each phase has distinct characteristics and demands, resulting in significant variations in their investment and innovation strategies (Miller & Friesen, 1984). However, firms at different FLCS make varied investment decisions and adopt unique technological advancements (Hou *et al.,* 2024). Therefore, it is plausible that the impact of AI technology on corporate ESG performance would differ across the phases of a firm's life cycle. In the introduction stage, firms prioritize survival, market establishment, and growth (Habib & Hasan, 2019). They do not focus on investment in diverse research and development due to a lack of infrastructure and the heavy investment required for AI technology. While, ESG is also considered a non-financial aspect (Hou *et al.,* 2024; Zahid *et al.,* 2023), so firms in this stage prioritize quick financial investment strategies to stay in market. This focus on growth and competitive positioning can overshadow sustainability initiatives (Habib & Hasan, 2019), leading to a reduced emphasis on ESG performance in introduction stage. As firms progress to the growth and mature stage, they encounter increased scrutiny from investors, customers, and regulators regarding their ESG practices. Based on the resource-based view theory (RBV), the research posits that integrating AI constitutes a valuable resource capable of significantly enhancing value creation and overall firm efficacy (Hussain *et al.,* 2024). AI emerges as a standout technology, offering diverse avenues for firm performance (Bosse *et al.,* 2023). As a result, firms in growth and mature stages invest more in technological initiatives to attain sustainable competitive advantages. Because firms in these stages are characterized by greater resource availability and a strategic focus on long-term sustainability (Habib & Hasan, 2019). By integrating AI technology, firms can effectively allocate funds and invest in potential ESG initiatives using diverse strategies, facilitating optimal financing and cost management (Macpherson et al., 2021). This strategic deployment of AI not only enhances financial efficiencies but also enables organizations to pursue ESG objectives without compromising revenue streams.

Finally, declining and shakeout firms typically have fewer resources to allocate toward ESG initiatives (Hou *et al.,* 2024). Most firms at this stage cut costs and reallocate resources away from technological advancements and ESG activities to focus on financial recovery, leading to a decline in ESG performance. Therefore, the impact of AI could negatively affect ESG performance due to the increased focus on short-term financial outcomes, resource constraints, heightened shareholder pressure, risk aversion, compensation adjustments favoring financial metrics, and stakeholder conflicts.

This study takes a distinct approach compared to prior studies on the relationship of digital transformation and ESG practices (Fang *et al.,* 2023; Lu *et al.,* 2023; Wang *et al.,* 2023). However, the uncertain measurement of digital transformation presents challenges, which currently relies only on financial variables and major technological components (Andriole, 2020). Recent research from Yang et al. (2024) and Li et al. (2024b) shows that AI offers superior comprehension compared to digital transformation, recognizing the interdependence of digital transformation on AI. Therefore, to enhance the responsiveness and impact of transformational initiatives, the study integrated AI technology across multiple dimensions. We have incorporated different key considerations include the depth and breadth of an organization's AI adoption, progress in developing AI capabilities, the use of the AI ecosystem, and the reconfiguration of organizational structures and procedures to accommodate new technologies.

Thus, to empirically explore the relationship between AI technology and the firms ESG performance, our research draws on a dataset comprising 10,821 firm-years observations within the Chinese A-share listed firm sample spanning from 2010 to 2020. The primary findings substantiate that the integration of AI into firm operations significantly and positively impacts ESG performance. Our analysis reveals that the influence of AI on firm ESG performance is notably heightened during the growth and maturity stages, whereas the introduction, decline, and shakeout stages exhibit no significant impact. Moreover, the study conducts a thorough exploration of the AI technology and ESG relationship through a dual-channel analysis. This study shows how AI improves ESG performance, thereby integrating its influence on ESG into its framework. The mediators linking AI adoption and sustainability practices are green innovation and firm performance. Green innovation made possible by AI drives which improves environmental practices and governance systems. Further supporting ESG commitments which are AI-driven efficiencies improving firm performance. The results demonstrate that AI fosters green innovation, leading to heightened investment in ESG initiatives. Likewise, AI's role in enhancing firm performance correlates with increased investment in ESG projects, underscoring its multifaceted impact on sustainability endeavors. Additionally, the heterogeneity analysis reveals intricate nuances in this nexus, indicating that the impact is more pronounced in non-state-owned enterprises (SOEs) compared to SOEs. While, this effect is particularly heightened in regions characterized by low bank concentration, as opposed to regions with high bank concentration. To ensure the validity of our main findings, we conducted various robustness tests, including alternative variable analysis, two-stage least squares, and propensity score matching. These tests were employed to mitigate any potential endogeneity concerns associated with our research outcomes.

Our research makes significant contributions to the existing literature in several ways. Firstly, existing studies predominantly revolve around DT as a significant catalyst for ESG (Chen & Hao, 2022; Fang *et al.*, 2023; Lu *et al.*, 2023; L. Wang *et al.*, 2022; Q. J. Wang *et al.*, 2023; Wang & Esperança, 2023; Wu *et al.*, 2023). However, the measurement of DT is inherently controversial (Andriole, 2020; Wu *et al.*, 2023). This controversy arises due to the vague calculation of DT, which encompasses financial variables and broader technological aspects only. Comparatively, we measure AI adoption from multiple dimensions, including the extent of a firm's adoption of AI technology scope, the development of AI capabilities, the utilization of the AI technological ecosystem coordination and the specification and reconfiguration of organizational structure and processes to facilitate technological change. Secondly, from ESG perspective it helps to clarify that how technological advancements affect a firms ESG performance. While many factors influencing ESG performance have been examined in recent years, such as national economic development (Naomi & Akbar, 2021), culture and institutional factors (Cai *et al*., 2016), enterprise-level factors like ownership structure (Ferrell et al., 2016), CEO characteristics and their incentives (Hegde & Mishra, 2019; Maqsood *et al.*, 2023), and legal origins (Liang & Renneboog, 2017), only few studies have focused on how technological innovation specifically influences ESG performance. In this context, our study aims to bridge this gap by adding contribution to ESG literature by examining the relationship between technological advancement and ESG performance. We provide insights into how AI technology influences ESG practices, thereby expanding our understanding of the broader implications of technological innovation on corporate sustainability. Thirdly, from AI perspective this study expands the existing literature, by delving into that how AI technology shapes contemporary firm practices. Economists have extensively discussed the incentives driving firms toward AI technology, including increased investment in research and development (Cihon, 2019), amplified firm innovation (Bahoo *et al.*, 2023), firm productivity (Czarnitzki et al., 2023), firm performance (Bosse *et al.*, 2023), and potential organizational restructuring (Bloom *et al.*, 2014). Thus, the study offers fresh insights by uncovering a significant relationship between ESG and the incorporation of AI technologies within firms. This highlights that AI not only reshapes internal processes but also influences external stakeholder relationships. Finally, this research takes a comprehensive approach for measuring AI, encompassing not only a broader spectrum of digital technologies, including traditional ones like information communication technology, machine learning, and big data, but also emerging automation technologies like robotics, and AI's cognitive decision-making capabilities. Apart from study contribution our research also provides vital insights for policymakers, managers and stakeholders aiming to leverage AI for sustainable firm practices. By incorporating these insights, policymakers can design supportive policies, managers can make informed investment decisions and stakeholders can back organizations driving AI-driven sustainable innovation. Ultimately, these efforts promote environmentally friendly practices in the digital economy, fostering a more sustainable future.

## Literature Review and Hypothesis Development

### *Drivers of ESG and AI Technology*

Many elements that affect a firm sustainability policies and long-term business value shapes the quest of good ESG performance. Researchers have investigated several important drivers over time: national economic development (Naomi & Akbar, 2021), cultural and institutional influences (Cai *et al.*, 2016), firm-specific characteristics including ownership structure (Ferrell *et al.*, 2016); CEO incentives (Hegde & Mishra, 2019; Maqsood et al., 2023); legal origins (Liang & Renneboog, 2017) and green innovation (Ali *et al.*, 2021). Notwithstanding this large-scale research, the influence of technology innovation especially AI in determining ESG performance is still little known.

However, environmental elements concentrate on carbon emissions, energy efficiency and resource use; companies work to minimize their environmental impact by means of programs such waste reduction and renewable energy acceptance (Fang *et al.*, 2023). Labor practices, diversity and inclusion, employee well-being, and ethical supplier chains all of which support business reputation and stakeholder confidence are among the social elements (Ahmed *et al.*, 2014). Conversely, governance issues on leadership, openness and risk management; measures such as board independence (Hegde & Mishra, 2019; Maqsood *et al.*, 2023), CEO pay plans and shareholder rights guarantee corporate responsibility.

Traditionally, companies have addressed these ESG issues with company policy and regulatory compliance. But the development of AI is radically changing how companies improve their ESG performance. By means of energy consumption, ecological risk prediction and resource management automation, AI-driven solutions maximize environmental sustainability (Frank, 2021). AI helps companies in the social sphere to monitor worker diversity, improve consumer interactions and guarantee ethical supply chain openness. From a governance standpoint, AI increases corporate control by means of automated compliance, fraud detection, and data-driven board level decision-making. Including AI into their ESG plans helps companies not only increase operational efficiency and environmental initiatives but also reduce risks and build closer stakeholder confidence. This paper investigates the transforming power of AI in matching business operations with sustainability objectives, therefore supporting the increasing conversation on technology innovation as a main facilitator of ESG performance.

### *Artificial Intelligence Technology and ESG Performance*

AI technology facilitates a transformative shift in corporate practices, fostering a culture of systematic innovation. It is commonly recognized as a viable tactic for attaining sustainable, long-term growth and innovation (Bahoo *et al.*, 2023; Roberts *et al.*, 2021), with robust ESG efforts being instrumental in driving enduring success (N. Wang *et al.*, 2022). By harnessing AI tools like big data, blockchain, and machine learning, enterprises enhance their ability to implement ESG principles across various facets of their operations. Firstly, on the one hand, this integration not only empowers enterprises with resources but also enables them to enhance their ESG performance through internal R&D advancements or the adoption of cutting-edge digital solutions. Through optimized resource utilization and precise monitoring of emissions, AI-driven initiatives facilitate pollution reduction, energy conservation and overall improvement in environmental performance, thereby reinforcing the commitment to sustainable business practices (Hussain *et al.*, 2024).

On the other hand, AI technology has a regulatory impact due to its capacity to significantly enhance data extraction, processing and interpretation, thereby augmenting managerial decision-making processes and operational efficiency (Solana-Gonzalez e*t al.*, 2021). As a result, it fosters greater transparency in information dissemination. Consequently, it serves as a deterrent against opportunistic behavior among managers, making it easier to identify and address actions that may have adverse social and environmental ramifications within organizations equipped with advanced AI infrastructure. Therefore, the integration of AI technology can contribute to the enhancement of corporate governance, thereby positively impacting firm ESG performance. Furthermore, as investors increasingly prioritize ESG performance (Thomas, 2008), poor ESG standings signal a lack of commitment to environmental and social responsibility, thereby diminishing a firm's appeal to potential investors. The incorporation of AI technologies within organizations amplifies information transparency, prompting firms to place greater emphasis on environmental and social responsibility performance. This is because AI facilitates easier access to ESG-related data for investors, ultimately driving firms to enhance their performance in these areas.

Secondly, the integration of AI technologies equips firms with a competitive edge and more effective risk management strategies, thereby enhancing ESG performance. While committing to ESG standards may initially impact a firms profitability and competitive positioning (McWilliams & Siegel, 2001; Zhang *et al.*, 2022), managers may opt to defer or avoid investing in ESG, in line with the principles of the RBV theory. According to this theory, the AI technology represents a substantial accumulation of valuable resources, prioritizing the establishment and support of competitive advantage for long-term organizational success (Giustiziero *et al.*, 2023; Lozano *et al.*, 2015). Importantly, AI-driven analytics enable firms to identify inefficiencies and minimize environmental impact by optimizing energy consumption, waste management, and sustainable sourcing (Günther *et al.*, 2017). Moreover, this theory underscores the significance of AI technology in fostering growth and value creation, surpassing other resources in terms of enduring competitive advantage. A pivotal aspect of AI is its capability to furnish organizations with valuable insights into industry dynamics, technological advancements and ESG opportunities. By tracking labor conditions, guaranteeing ethical supplier chains, and supporting workplace diversity via objective recruiting algorithms, AI also improves social responsibility. Regarding governance, AI increases compliance and openness by means of fraud detection, corporate disclosure analysis, and regulatory standard adherence assurance. Incorporating AI as a useful tool would help companies to get a competitive edge in ESG performance, therefore promoting long-term sustainability and stakeholder confidence. Leveraging this informational advantage, enterprises are motivated to enhance their ESG initiatives, enabling them to make informed decisions and maintain competitiveness within a dynamic firm environment. This strategic utilization of AI empowers firms to cultivate lasting value and thrive within their respective sectors (Helfat *et al.*, 2023), thereby encouraging and incentivizing the implementation of ESG activities.

Thirdly, AI integration plays a pivotal role in reshaping the corporate innovation landscape (Bahoo *et al.*, 2023), enhancing organizations capacity for autonomous innovation while nurturing an ethos of openness and collaboration. This innovative approach embodies the firm's dedication to sustainable development, exemplifying its commitment to initiatives such as green innovation (GI). The AI technology can bolster a firms capability for GI (Hussain *et al.*, 2024), thereby enhancing its ESG performance. GI encompasses the development of processes, technologies, or products aimed at minimizing environmental impact while enhancing energy and resource efficiency (Schiederig *et al.*, 2012). Leveraging cutting-edge technologies, firms can optimize various aspects of their production processes, including research and design, manufacturing and raw material utilization (Wu et al., 2016). Furthermore, they can utilize big data, AI and similar technologies to effectively monitor and control corporate emissions, as well as to quantify price and trade carbon emissions (He *et al.*, 2023). This AI adoption by firms holds the potential to enhance their capacity for GI, thereby augmenting their technical proficiency in fulfilling environmental and social responsibilities, ultimately leading to an enhancement in their ESG performance.

Lastly, the integration of AI technology significantly enhances firms performance, transforming various operational aspects (Bosse *et al.*, 2023), which in turn enhance ESG performance. Because, AI facilitates data-driven decision-making, process optimization and heightened operational efficiency. By leveraging advanced analytics and machine learning algorithms, AI identifies patterns, predicts outcomes and automates tasks, reducing errors and enhancing productivity (Czarnitzki *et al.*, 2023). Additionally, AI delivers personalized customer experiences, elevates product quality and fosters innovation (Yang *et al.*, 2024). This improved performance across operational, customer-facing and strategic domains contributes to enhanced ESG performance for firms. While, AI aligns with ESG principles by streamlining processes, reducing waste and fostering sustainable practices, thereby fostering long-term value creation and resilience in a complex corporate landscape. Based on the above-aforementioned insights we formulate our first hypothesis.

**H1:** Artificial intelligence technology can improve firms ESG performance.

### *AI Technology, ESG Performance and Firm Life Cycle Stages*

Previous research has segmented the firm's life cycle stages (FLCS) into five distinct phases: introduction, growth, maturity, decline, and shakeout. These stages are pivotal in understanding a firm's trajectory, profitability and risk profile, as highlighted by Dickinson (2011b), who emphasizes the significance of operational, investment and financing cash flows in this assessment. From theoretical point of view, growth models suggest that organizations undergo a progression through various stages, each marked by distinct competitive and institutional challenges, starting from birth to eventual decline. As a result, a firm's objectives, strategies and performance continually evolve throughout its life cycle stages, reflecting its response to the challenges and opportunities encountered at each phase (DeAngelo *et al*., 2010).

While, the central theoretical premise of this study is that firms orientation and resource allocation towards discretionary expenditures, such as ESG initiatives and digital technologies, follow a systematic pattern depending on its position within the corporate life cycle continuum (Ahmed *et al.,* 2020). From a practical standpoint, this suggests that managers need to customize their approach to AI technology and ESG planning based on the firm's current maturity level. The strategies pursued by introductory firms may differ significantly from those firms in decline. Consequently, policy recommendations should consider the firms' stages of development. By integrating FLCS into our research methodology allows for a more nuanced analysis of the relationship between AI technology and ESG practices throughout the firm's development trajectory. While corporate ESG initiatives can enhance management motivation and firm performance, it is crucial to recognize that the availability of resources for ESG implementation and its prioritization may vary as firms progress through different stages of development and face diverse competitive landscapes (Habib & Hasan, 2019). Thus, we hypothesize that the impact of AI on ESG performance is influenced by different FLCS.

In the introduction phase of FLCS, the ability of firms to maintain financial stability are significantly influenced by corporate investment decisions. The study argues that during this early stage, the implementation of AI has minimal positive impact on ESG performance. Because firms in their infancy often experience negative cash flows from both operations and investments, relying heavily on equity, private investments and internal funds (Adizes, 2004; Dickinson, 2011b). Whether a firm is adopting AI technology voluntarily or engaging in ESG initiatives, its primary objective is typically survival in the market. Consequently, such firms tend to refrain from making impulsive decisions regarding the deployment of ESG. Thus, we propose the following hypothesis.

***H2a:*** *AI technology does not impact firms ESG performance during introduction stage.*

Furthermore, during the "growth stage" firms experience robust cash flows from operations stemming from significant sales volumes, a solid market reputation and high profitability (Dickinson, 2011b). However, firms in this stage of their life cycle endeavor to integrate AI and engage in ESG activities, empowered by their improved resource allocation capabilities and heightened motivation to pursue lucrative endeavors.

***H2b:*** *AI technology impact firms ESG performance during growth stage.*

While, firms that are in the "maturity stage" of their life cycle are usually in a position where they may engage aggressively in digital technologies and ESG efforts since they have consistent cash flows and are financially secure. Considering that some research indicates that investors could be more interested in expanding businesses that are more visible to the market (Habib & Hasan, 2019). However, from the stakeholder's perspective which indicates that while ESG may not alter significantly at this level, management of established firms may have distinct reasons for participating in it (Hussain *et al.,* 2026). Consequently, we hypothesize that because of their proven digital capabilities and financial flexibility, mature firms show the most notable gains in the link between AI technology and ESG performance.

***H2c:*** *AI technology significantly impact firms ESG performance at maturity stage.*

In the final phase, referred to as the "shakeout and decline stage," firms face a decline in resources as their profitability and product lines weaken (Miller & Friesen, 1984). These firms are typically larger, more established, inflexible and struggling. Even though declining firms are reluctant to reduce their discretionary spending on ESG initiatives during tough times, their options are limited. This is because firms in decline tend to follow a pattern similar, to that of introductory firms in their different strategies like AI and ESG practices. In such circumstances, the primary focus of the firm is often on survival rather than on long-term initiatives such as ESG. In addition, firms may encounter difficulties integrating AI successfully during downturns as a result of budgetary restrictions, organizational lethargy, or a lack of strategic focus.

In the shakeout stage, firms are constantly reorganizing and changing their structures to improve their operations and find new ways to stand out in the market. Because resources may be redirected to manage internal transitions instead of pursuing long-term sustainability goals, these organizational changes might impede the creation of unified ESG policies and delay the execution of AI projects. This may further reduce the possible influence of AI technology on ESG performance.

***H2d:*** *AI technology does not impact firms ESG performance at declining and shakeout stages.*

The study utilizes figure 1 to visually depict a conceptual framework, which intuitively aids in presenting a logical progression of hypothesis development. Additionally, table 1 provides measurements of all FLCS, further enhancing understanding.

Table 1

**Firm Life Cycle Using (Dickinson, 2011a) Model**

| FLCS | | Introduction | Growth | Maturity | Decline | Shake-out |
|---|---|---|---|---|---|---|
| **Cash Flow** | *CFO* | - | + | + | + | +/- |
| **Patterns** | *CFI* | - | - | - | + | -/+ |
| | *FCF* | + | + | - | +/- | -/- |

***Note**: This table illustrates the measurement of firm life cycle stages (FLCS) using cash flow patterns. CFO represents cash flow from operations, CFI displays cash flow from investing activities, and CFF indicates cash flow from financial activities.*

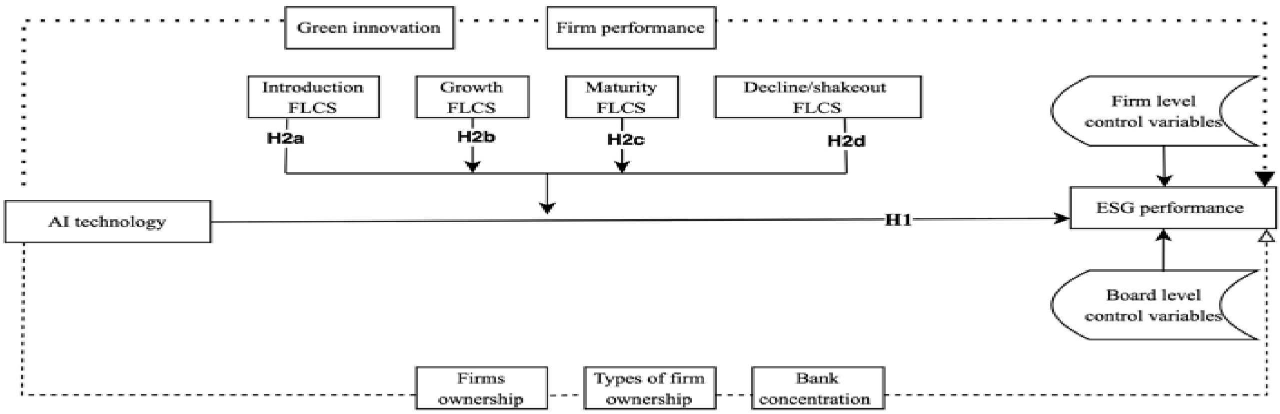


**Figure 1.** Solid Lines Depict the Direct Impact of Artificial Intelligence Adoption on Firm ESG Performance. Conversely, Dotted Lines Illustrate Channel Analysis, While Dashed Lines Represent Heterogeneity Analysis

## Research Data and Methodology

### *Data and Sample*

The empirical analysis of this study draws on a data from Chinese A-share listed firms covering the period from 2010 to 2020. This specific timeframe was selected because it coincides with the voluntary disclosure of ESG aspects by Chinese A-listed firms, which commenced in 2010. Following the previous studies on ESG (Hou *et al.*, 2024; Maqsood *et al.*, 2023), we collect the ESG data from Bloomberg database. Furthermore, data regarding AI technology were extracted from CNINFO datasets, an officially authorized website by the China securities regulatory commission for listed firms' information disclosures and financial indicators data from China stock market & accounting research (CSMAR). To ensure the accuracy of the analysis and minimize the potential influence of outliers, we carefully processed the original sample. Firstly, we handled samples from the financial sector using following criteria: we excluded all samples from this sector, removed samples with financial anomalies such as those categorized as ST (special treatment) status or with a leverage ratio exceeding one, and eliminated samples lacking essential characteristics. Furthermore, we applied winsorizing to all major continuous variables, adjusting extreme values at both the upper and lower 1 % levels (Hou *et al.*, 2024). After applying these criteria, the final sample was consisted on 10,821 firm-year observations.

### *Variable Measurement*

### *Dependent Variable*

To measure ESG indicators and have an accurate panel Bloomberg relies on various publicly accessible sources such as annual reports, sustainability reports and company websites (Hou *et al.*, 2024; Maqsood *et al.*, 2023; Zahid *et al.*, 2023). In this study, the dependent variable consists of the environmental, social, and governance (ESG) scores obtained from Bloomberg, along with their three individual components (E, S, and G). The Bloomberg ESG disclosure ratings, serving as a composite index, offer a comprehensive evaluation encompassing both financial and non-financial aspects. Specifically, Bloomberg collects ESG information disclosed by companies through various channels, including corporate websites, CSR or sustainability reports, annual reports, and other accessible sources. The environmental dimension of the indexes encompasses various elements such as waste management, water resources management, energy consumption, ecological impact, and air quality. Meanwhile, the social component encompasses community engagement, diversity and inclusion practices, ethical conduct, employee welfare, and supply chain management procedures. Lastly, the governance dimension covers aspects like board tenure, diversity, independence, oversight of audits, board composition, remuneration policies, and governance practices related to sustainability. Moreover, they occasionally directly approach relevant firms to obtain necessary data. Employing Bloomberg's evaluation methodology, over 120 data points are meticulously assessed, aggregated and standardized to derive the overall ESG score and its respective subcategories (Hou *et al.*, 2024; Maqsood *et al.*, 2023; Zahid *et al.*, 2023). However, firms with no ESG data at all receive a score of 0, while those with complete data disclosures receive a score of 100 and continuous variables "winsorized" at the 1 % level to mitigate the impact of outliers on the outcomes.

*Independent Variable*

AI technology is challenging to quantify due to its widespread use and constantly evolving nature, making it difficult to gather information about its adoption and impact within firms. However, scholars and researchers have employed text-mining techniques to assess AI. Specifically, computer-assisted textual analysis (CATA) software tools count the frequency of keywords in texts (Hussain *et al.*, 2024; Li *et al.*, 2024a, 2024b; Younas *et al.*, 2025). As this study focuses on Chinese firms, we utilized Python code (crawler) and conducted text analysis on annual Chinese reports downloaded from CNINFO and obtain keyword frequencies related to AI. By following previous research using CATA, we established an AI proxy through a series of steps.

Phase 1: Formulating the initial lexicon

Initially, we utilized the "China artificial intelligence industry analysis report 2020" as a foundational resource to establish an initial lexicon. Subsequently, we employed deep learning techniques to recommend synonyms, ensuring comprehensive coverage while avoiding the omission of crucial terms and expressions. Specifically, terms such as "artificial general intelligence," "deep learning," and "neural network" were integrated into the original lexicon. Additionally, we incorporated high-frequency words and phrases derived from sample texts through an inductive process, adhering to the methodologies outlined by Hussain et al. (2024) and Li et al. (2024b). Concepts such as "human-computer interaction" and "image recognition" were amalgamated during this induction phase. This systematic approach resulted in the creation of a preliminary lexicon comprising 73 words and phrases.

Phase 2: Lexicon screening and refinement

Secondly, we conducted a meticulous review to identify and eliminate terms or phrases deemed unclear or overly broad, following the methodology outlined by Hussain et al. (2024), Yang et al. (2024) and McKenny et al. (2018). Each author meticulously scrutinized the text, removing words and sentences perceived as disjointed or lacking coherence. In instances where disagreement arose regarding the relevance of a term, the entire author team engaged in thorough deliberation until a consensus was reached regarding its inclusion or removal. Consequently, terms such as "planning and scheduling," "digitization technology," "digital communication," "digital currency," "digital technology," "platform," "recommender systems," and others were excised during this process. Additionally, to ensure the representativeness of the lexicon, terms and phrases occurring fewer than fifteen times were also eliminated. Examples of less frequently referenced terms included "automated reasoning," "artificial immune system," "Bayesian network," and "artificial consciousness." This comprehensive review resulted in the removal of 20 terms or phrases, culminating in a final Chinese vocabulary comprising 53 words.

Phase 3: Final AI proxies

Following methodologies outlined by Hussain et al. (2024), Yang et al. (2024) and Babina et al. (2021), we conducted an assessment of the overall word frequency within the lexicon. To ascertain the adoption of AI technology within businesses, we developed three proxies.

- AI_TEXT: Generated by natural logarithm of 1 plus the frequency of AI keywords
- AI_DUM: AI_DUM is a binary variable that takes the value 1 if a firm adoption of AI technology in MD&A and 0 otherwise. We designate AI_DUM=1 for a firm at year t and all following years if the firm starts adopting AI at that time.
- AI_IV: For endogeneity, we use the natural logarithm of 1 plus the average frequency of AI keywords in the industry and year.

*Firm life cycle stages variables*

To measure the stages of a firm's life cycle, this study utilized the Dickinson (2011b), cash flow method, which involves firm cash flow dynamics including operating cash flow, investment cash flow, and financing cash flow. This method is widely used in existing studies, as noted by Hou et al. (2024) and Maqsood, Li, Younas and Amjad (2026). By following these studies, this research incorporated five stages of the firm life cycle stages, namely introduction, growth, maturity, decline, and shakeout. These stages reflect the overall phases of a firm from birth to decline, as illustrated in table 1.

*Control Variables*

To comprehensively investigate the relationship between AI and ESG performance, this study meticulously controls for important key variables across firm and board levels, as highlighted in prior studies (Maqsood, Li, Younas, Hussain, *et al.*, 2026; Yang *et al.*, 2025; Zahid *et al.*, 2025). These variables include firm size (Size) is measured as the natural logarithm of total assets, reflecting the potential differences in resources and strategies between larger and smaller firms as larger firms have more competitive advantage and stakeholder attention. Firm leverage (Lev) is defined as the ratio of total debt to total assets, indicating a firm's financial stability and risk profile. Firm sales (Ln (sales) are assessed through the natural logarithm of revenue growth rate, illuminating the scale of operations and market penetration. The cash ratio (CR), derived from cash and cash equivalents divided by total assets, offers insights into liquidity and short-term liability coverage of the firm. While, firm age (Age) is computed as the natural logarithm of years since listing date plus one, that capture the temporal aspect of firm existence. Additionally, research and development expenditures (R&D) and property, plant, and equipment (PPE) represent investments in innovation and tangible assets, respectively. Moreover, we included board-level control variables in this study. Independence director (IND), which is determined by taking the natural logarithm of the independent directors, and board size (BS), which is determined by taking the natural logarithm of the total number of directors on the board, because larger boards tend to have a higher probability of engaging in ESG initiatives (Hou et al., 2024; Maqsood et al., 2023; Zahid et al., 2023). We also used CEO duality, which is a dummy variable that equals one if the CEO also holds the position of Chairman and zero otherwise. See table 2 for more explanation of these variables.

Table 2

**Variable Definition and Explanation**

| Type | Variable | Definition |
|---|---|---|
| **Dependent variable** | | |
| ESG | Environmental, social, and governance | Bloomberg's ESG total score ranges between 0 and 100 |
| E | ESG environment component | The environmental activity total score of Bloomberg spans from 0 to 100. |
| S | ESG social component | Bloomberg's social activity overall score falls within the range of 0 to 100. |
| G | ESG governance component | Bloomberg's governance activity total score ranges between 0 and 100 |
| **Firm life cycle stages variable** | | |
| Introduction | Introduction stage | Introduction stage of firm life cycle, following Dickinson cashflow pattern in table 1. |
| Growth | Growth stage | Growth stage of firm life cycle, following Dickinson cashflow pattern in table 1. |
| Maturity | Maturity stage | Maturity stage of firm life cycle, following Dickinson cashflow pattern in table 1. |
| Decline | Decline stage | Decline stage of firm life cycle, following Dickinson cashflow pattern in table 1. |
| Shake-out | Shakeout stage | Shakeout stage of firm life cycle, following Dickinson cashflow pattern in table 1 |
| **Dependent variable** | | |
| AI | Artificial intelligence (AI) technology | AI_DUM is a binary variable that takes the value 1 if a firm adoption of AI in MD&A and 0 otherwise. We designate AI_DUM=1 for a firm at year t and all following years if the firm starts adopting AI at that time. |
| **Firm and board level control variable** | | |
| Size | Firm size | Firm size calculated as in (total Assets) |
| Lev | Leverage | Calculated by total debts over total assets |
| Ln(sales) | Firm sales | The logarithm of the total revenue growth rate of the firm |
| Age | Firm age | The natural logarithm of the time elapsed since the listing date plus one equals the age of the firm |
| CR | Cash ratio | Determined by dividing cash and cash equivalents by total assets |
| R&D | Research & development | Total research and development expenditures |
| PPE | Property and plant equipment | Total sum of property, plant, and equipment |
| Duality | CEO duality | A binary indicator denoting CEO duality, with a value of 1 if the CEO concurrently holds the position of Chair of the Board, and 0 otherwise |
| BS | Board size | Board size is determined by computing the natural logarithm of the total count of directors serving on the board |
| IND | Independence board | Board Independence is computed by dividing the count of independent directors by the total number of board members |
| Bank | Bank concentration regions | we denote the number of bank branches per capita in province c in year $_{t-1}$ as Bank $_{c,t-1.}$ |

*Econometric Model*

To check the impact of AI on ESG performance, we employ the baseline model (1), as our testing ground for hypothesis 1.

$$ESG_{it} = \alpha + \beta_1 AI_{it} + \beta_2 Size_{it} + \beta_3 Lev_{it} + \beta_4 Ln(sales)_{it} + \beta_5 Age_{it} + \beta_6 CR_{it} + \beta_7 R\&D_{it} + \beta_8 PPE_{it} + \beta_9 Duality_{it} + \beta_{10} BS_{it} + \beta_{11} IND_{it} + \omega_{year} + \omega_{Industry} + \varepsilon_{it} \quad (1)$$

Where in equation (1), each firm is identified with a unique subscript "$i$", while "$t$" denotes the observation year. $ESG_{it}$ represents firm environmental, social, and governance, while AI denotes the firm artificial intelligence adoption. Various factors such as Size, Lev, Ln(sales), Age, CR, R&D, PPE, Duality, BS and IND used as a set of control variables as explain in section 3.2.4. Moreover, the model also accounts for time-fixed effects with $\omega_{year}$ and includes $\omega_{Industry}$ as a dummy variable to address industry-fixed effects. Finally, any unexplained variations are represented by the random error term $\varepsilon_{it}$.

$$ESG_{it} = \alpha + \beta_1 AI_{it} + \beta_2 FLCS_{it} + \beta_3 Size_{it} + \beta_4 Lev_{it} + \beta_5 Ln(sales)_{it} + \beta_6 Age_{it} + \beta_7 CR_{it} + \beta_8 R\&D_{it} + \beta_9 PPE_{it} + \beta_{10} Duality_{it} + \beta_{11} BS_{it} + \beta_{12} IND_{it} + \omega_{year} + \omega_{Industry} + \varepsilon_{it} \quad (2)$$

To explore hypothesis H2a-H2d, we employed equation (2) to examine how AI technology influences ESG performance throughout different phases of a firm's life cycle. In this equation, FLCS represents the five stages of the firm life cycle: introduction, growth, maturity, decline and shakeout.

## Empirical Results

*Descriptive Statistics*

Table 3 presents the summary statistics for the all variables of the study, including ESG performance, AI technology and FLCS, along with the firm and board level control variables. In panel A, wide spectrum of ESG practices is evident within Chinese enterprises, with a mean ESG score of 20.83 and a standard deviation of 7.133. This range, spanning from 1.24 to 64.115, highlights the diverse commitment levels to ESG performance. The observed variance suggests a need for greater awareness and incentive to enhance ESG disclosure and transparency nationwide. While, panel B presents information regarding FLCS, with the selected sample comprising 28% growth firms and 32%

mature firms, aligning with findings from the study by Shahzad et al. (2022). Moving to panel C, the average AI rate stands at 0.218, implying that around 21% of the selected firms have extensively incorporated AI into their operations. However, the standard deviation of 0.413 suggests considerable variability in AI technology levels across organizations, ranging from comprehensive integration to minimal utilization. Panel D provides summary statistics for control factors, which include company financial and governance attributes.

Table 3

**Summary Statistics**

| | Mean | Median | Std. Dev. | min | max | N |
|---|---|---|---|---|---|---|
| **Dependent variable Panel A** | | | | | | |
| ESG | 20.83 | 19.835 | 7.133 | 1.24 | 64.115 | 10821 |
| E | 11.082 | 9.302 | 8.134 | .775 | 65.625 | 10821 |
| S | 23.645 | 22.807 | 9.905 | 3.509 | 77.193 | 10821 |
| G | 45.193 | 44.643 | 5.401 | 3.571 | 73.214 | 10821 |
| **Firm life cycle stages variable** | | | | | | |
| Intro-FLCS | .101 | 0 | .301 | 0 | 1 | 10821 |
| Gro-FLCS | .282 | 0 | .450 | 0 | 1 | 10821 |
| Mat-FLCS | .327 | 0 | .472 | 0 | 1 | 10821 |
| Dec-FLCS | .026 | 0 | .159 | 0 | 1 | 10821 |
| Shake-FLCS | .034 | 0 | .160 | 0 | 1 | 10821 |
| **Independent variable** | | | | | | |
| AI | .218 | 0 | 0.413 | 0 | 1 | 10821 |
| **Firm and board level control variable Panel B** | | | | | | |
| Size | 21.888 | 21.718 | 1.314 | 18.266 | 26.452 | 10821 |
| Lev | .446 | .433 | .247 | .026 | 3.805 | 10821 |
| Ln(sales) | 21.192 | 21.077 | 1.515 | 16.049 | 25.869 | 10821 |
| Age | 2.05 | 2.197 | .858 | 0 | 3.401 | 10821 |
| CR | .168 | .128 | .136 | .001 | .841 | 10821 |
| R&D | 4.525 | 3.53 | 4.783 | 0 | 32.54 | 10821 |
| PPE | .232 | .198 | .171 | .001 | .817 | 10821 |
| Duality | .277 | 0 | .448 | 0 | 1 | 10821 |
| BS | 8.691 | 9 | 1.868 | 0 | 24 | 10821 |
| IND | 35.666 | 33.33 | 8.780 | 0 | 100 | 10821 |

***Note**: This table provides summary statistics for all variables used in this study. The first three columns display the mean, median, and standard deviation, while the last three columns show the minimum, maximum, and number of observations.*

*Correlation Matrix*

Table 4 presents the correlation matrix results, unveiling significant findings. Notably, the subcomponents of firms ESG performance exhibit substantial and statistically significant positive correlations, indicating a robust interconnection among these factors. Additionally, a noteworthy positive association emerges between AI technology and ESG performance, along with its subcomponents. Moreover, the reliability of the control set is underscored by the significant relationships observed between most of our control variables and ESG metrics. This evidence indicates that our model does not demonstrate multicollinearity.

*Baseline Regression: AI Technology and Firm ESG Performance*

Table 5 presents the baseline regression findings concerning AI and ESG performance, alongside its individual components (E, S, and G), revealing a significantly positive in column 1 with a coefficient of 1.035***, at the 1% significance level after accounting for year and firm effects. This suggests that AI technology facilitates improved ESG performance. Furthermore, there are notable positive associations between AI and ESG subcomponents, including environment (E=1.113***), social (S=1.468***) and governance (G=.915***). These findings lend strong support to hypothesis 1, indicating that the integration of AI into firms' processes has a significant impact on ESG economic implication. For example, based on the data from table 4, ESG has an average value of 20.83 and AI technology with standard deviation of 0.413. Thus, ESG performance improves by 2.05% for every one standard deviation increase in AI, as indicated in column 1 of table 5 using the coefficient (1.035) = (1.035 × .413) / 20.83. These baseline findings suggest that firms experience enhanced ESG performance with the adoption of new technologies, particularly AI, which could attract sustainability-minded investors. Additionally, the statistical significance of other control variables regarding ESG and its components aligns with previous research (Hou *et al.*, 2024; Zahid *et al.*, 2023).

*AI Technology, ESG Performance and Firm Life Cycle Stages*

Afterwards, the study investigated the impact of AI technology on ESG performance and its sub-factors across various phases of a FLCS, including the introduction, growth, maturity, decline and shakeout phases (Dickinson, 2011b). The analysis employed five separate panels, yielding different results, as depicted in table 6. Panels A, B, C, D, and E illustrate the impact of AI on ESG performance across all these five phases, with year and industry fixed effects incorporated into all models. During the introductory stage of AI technology, indicated in the columns 1-4 of table 6, the coefficient (1.236) for AI with ESG are not statistically significant.

Table 4

**Correlation Matrix**

| | ESG | E | S | G | AI | Size | Lev | Ln (sales) | Age | CR | R&D | PPE | Duality | BS | IND |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ESG | 1 | | | | | | | | | | | | | | |
| E | .925*** | 1 | | | | | | | | | | | | | |
| S | .799*** | .598*** | 1 | | | | | | | | | | | | |
| G | .554*** | .382*** | .337*** | 1 | | | | | | | | | | | |
| AI | .0260* | .00760 | .0518*** | .00247 | 1 | | | | | | | | | | |
| Size | .439*** | .396*** | .316*** | .387*** | .0389** | 1 | | | | | | | | | |
| Lev | .161*** | .133*** | .0982*** | .205*** | -.00547 | .524*** | 1 | | | | | | | | |
| Ln (sales) | .430*** | .397*** | .307*** | .358*** | .0326** | .901*** | .519*** | 1 | | | | | | | |
| Age | .156*** | .124*** | .0642*** | .275*** | .00857 | .308*** | .255*** | .273*** | 1 | | | | | | |
| CR | -.0565*** | -.0569*** | -.0343** | -.0287* | .0865*** | -.183*** | -.354*** | -.147*** | -.162*** | 1 | | | | | |
| R&D | -.0744*** | -.0617*** | -.0350** | -.121*** | .248*** | -.241*** | -.288*** | -.313*** | -.189*** | .206*** | 1 | | | | |
| PPE | .0973*** | .114*** | .0225 | .0519*** | -.202*** | .0988** | .111*** | .103*** | .101*** | -.366*** | -.234*** | 1 | | | |
| Duality | -.0820*** | -.0529*** | -.0742*** | -.0943*** | .0488*** | -.133*** | -.124*** | -.135*** | -.160*** | .0115 | .160*** | -.0700*** | 1 | | |
| BS | .0990*** | .0790*** | .0740*** | .108*** | -.00772 | .225*** | .129*** | .208*** | .0986*** | -.0552*** | -.124*** | .166*** | -.152*** | 1 | |
| IND | .0566*** | .0521*** | .0425*** | .0503*** | .00133 | .113*** | .0556*** | .0855*** | -.0176 | .0338** | .0313* | -.0361** | .0731*** | -.389*** | 1 |

Table 5

**Baseline Regression: AI and firm ESG performance**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | ESG | E | S | G |
| AI | 1.035*** | 1.113*** | 1.468*** | .915*** |
| | (.202) | (.297) | (.284) | (.162) |
| Size | 1.745*** | 1.604*** | 2.047*** | 1.318*** |
| | (.197) | (.297) | (.278) | (.158) |
| Lev | -2.942*** | -2.329*** | -3.95*** | -2.97*** |
| | (.54) | (.807) | (.756) | (.433) |
| Ln(sales) | .654*** | 1.131*** | .825*** | -.111 |
| | (.168) | (.254) | (.237) | (.135) |
| Age | 3.319*** | 3.401*** | 3.033*** | .17 |
| | (.207) | (.327) | (.304) | (.166) |
| CR | 2.691*** | 2.949*** | 1.922** | 4.002*** |
| | (.647) | (.989) | (.915) | (.519) |
| R&D | .097*** | .161*** | .134*** | .015 |
| | (.023) | (.04) | (.033) | (.019) |
| PPE | 1.263* | .965 | 2.032* | -.48 |
| | (.752) | (1.072) | (1.049) | (.603) |
| Duality | -.135 | -.166 | -.147 | -.076 |
| | (.164) | (.246) | (.23) | (.132) |
| BS | -.211*** | -.268*** | -.085 | -.162*** |
| | (.055) | (.079) | (.077) | (.044) |
| IND | -.005 | -.013 | .011 | -.004 |
| | (.014) | (.019) | (.019) | (.011) |
| _cons | -40.019*** | -57.33 | -48.629*** | 18.658*** |
| | (2.783) | | (3.936) | (2.232) |
| Industry FE | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES |
| Observations | 10821 | 10821 | 10821 | 10821 |
| R-squared | .237 | .149 | .153 | .066 |

Note: Standard errors are shown in parentheses, with significance levels indicated as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

This suggests that in the early stages of a firm life cycle, resources are primarily directed towards establishing product viability and market presence. Consequently, there may be limited experience or capacity to address complex challenges such as integrating ESG factors or AI. However, the findings become favorable during the growth and maturity stages, evidenced by the 1% and 10% level of significance and a statistically positive with coefficient of 1.487*** in panel B and with coefficient .706* in a panel C of table 6 respectively. This suggests that as a firm advances into the growth and maturity stages, it consolidates significant resources and market influence. During this phase, there is substantial investment in AI to enhance competitiveness and efficiency. Simultaneously, there is a concerted effort to integrate ESG factors to maintain stakeholders' confidence and meet sustainability standards. Furthermore, in panel D and E of table 7, the results pertaining to the decline and shakeout stages demonstrate that both AI and ESG performance exhibit statistically insignificant but positive coefficients 0.917 and 2.004, respectively.

This underscores how during these stages of the FLCS, firms prioritize survival amidst existential threats and financial constraints, consequently diverting attention away from strategic initiatives such as AI and ESG integration. This shift in focus towards survival strategies, cost-cutting measures, and restructuring efforts diminishes resources and capacity available for long-term sustainability and technological advancement. These findings also validate our hypothesis 2 across various FLCS.

**Mechanism Analysis**

*Mediating Effect of Green Innovation*

Following the methodology employed in prior research (Hussain et al., 2024; Maqsood et al., 2024), the annual count of GI patent was employed as an index to gauge firm GI capabilities, defined as GI = ln (number of green patent applications + 1). Adoption of GI powered by AI immediately improves ESG performance. Environmentally, AI helps companies lower their carbon footprint, cut energy use, and apply sustainable resource management, thereby enhancing environmental measurements. Socially, companies which adopt AI-enabled GI draw investors and consumers who value sustainability, therefore strengthening their company brand and ties to stakeholders (Long et al., 2023). While, by offering insights into sustainable initiatives, therefore strengthening corporate responsibility and long-term planning, AI-driven data analytics also enhance governance frameworks. Equations (3) and (4) are derived from equation (1).

$$GI_{it} = \alpha + \beta_1 AI_{\text{it}} + \beta_2 Size_{it} + \beta_3 Lev_{it} + \beta_4 Ln(sales)_{it} + \beta_5 Age_{it} + \beta_6 CR_{it} + \beta_7 R\&D_{it} + \beta_8 PPE_{it} + \beta_9 Duality_{it} + \beta_{10} BS_{it} + \beta_{11} IND_{it} + \omega_{year} + \omega_{Industry} + \varepsilon_{it} \tag{3}$$

$$ESG_{it} = \alpha + \beta_1 AI_{\text{it}} + \beta_2 GI_{\text{it}} + \beta_3 Size_{it} + \beta_4 Lev_{it} + \beta_5 Ln(sales)_{it} + \beta_6 Age_{it} + \beta_7 CR_{it} + \beta_8 R\&D_{it} + \beta_9 PPE_{it} + \beta_{10} Duality_{it} + \beta_{11} BS_{it} + \beta_{12} IND_{it} + \omega_{year} + \omega_{Industry} + \varepsilon_{it} \tag{4}$$

Table 7 illustrates the results of regression analysis, indicating that GI capacity functions as a mediator between the adoption of AI and firms ESG performance. For instance, in column (1), the regression analysis reveals a significant positive impact of AI adoption on GI (coefficient = .032, $p < 0.05$), suggesting a substantial enhancement in corporate GI potential due to AI adoption, which support the findings of (Hussain et al., 2024). Furthermore, the findings in column (2) suggest that firms can improve their ESG performance by bolstering their GI capabilities. The coefficient of GI on ESG performance is .421, statistically significant at the 1% level. Even after controlling for industry and year fixed effects in columns 1–5, the positive effect of AI adoption on ESG performance persists in columns 2, along with GI as mediator on ESG performance and its components. These results support the premise of this study, affirming that AI adoption augments their capacity for GI (Hussain et al., 2024), consequently enhancing their ESG performance.

*Mediating Effect of Firm Performance*

Furthermore, this study utilized return on assets (ROA), calculated as net income divided by total assets to evaluate the mediating role of firm performance between AI technology and ESG. Building on the findings of Bosse et al. (2023), which highlighted the significant enhancement of firm performance through AI, we postulated that AI would influence ESG performance through its impact on firm performance

Equation 1 was employed to integrate equations (5) and (6) into the analysis, demonstrating the pathway through which ESG is influenced by AI via firm performance.

$$ROA_{it} = \alpha + \beta_1 AI_{\text{it}} + \beta_2 Size_{it} + \beta_3 Lev_{it} + \beta_4 Ln(sales)_{it} + \beta_5 Age_{it} + \beta_6 CR_{it} + \beta_7 R\&D_{it} + \beta_8 PPE_{it} + \beta_9 Duality_{it} + \beta_{10} BS_{it} + \beta_{11} IND_{it} + \omega_{year} + \omega_{Industry} + \varepsilon_{it} \tag{5}$$

$$ESG_{it} = \alpha + \beta_1 AI_{\text{it}} + \beta_2 ROA_{\text{it}} + \beta_3 Size_{it} + \beta_4 Lev_{it} + \beta_5 Ln(sales)_{it} + \beta_6 Age_{it} + \beta_7 CR_{it} + \beta_8 R\&D_{it} + \beta_9 PPE_{it} + \beta_{10} Duality_{it} + \beta_{11} BS_{it} + \beta_{12} IND_{it} + \omega_{year} + \omega_{Industry} + \varepsilon_{it} \tag{6}$$

Table 7 presents the outcomes of regression analysis, revealing that ROA serves as a mediator between AI and firms ESG performance. For instance, in column (6), the analysis unveils a significant positive impact of AI on ROA, with a coefficient of 0.01, at 1 % significance level, thus indicating a noteworthy improvement in firm performance attributed to AI.

Table 6

**AI and Firm ESG Performance with Respect to Firm Life Cycle Stages**

**Panel A:** Introduction stage of firm life cycle

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | ESG | E | S | G |
| AI | 1.236 | .337 | 3.45** | 1.531** |
| | (.78) | (.91) | (1.345) | (.74) |
| Size | .5 | .931 | .461 | .309 |
| | (.681) | (.835) | (1.162) | (.647) |
| Lev | 2.821 | -.04 | 4.947 | -1.046 |
| | (2.147) | (2.599) | (3.71) | (2.037) |
| Ln(sales) | 1.103* | .258 | 1.904* | 1.45** |
| | (.615) | (.851) | (1.063) | (.584) |
| Age | 2.334*** | 2.413** | 3.106** | -1.29* |
| | (.813) | (.983) | (1.513) | (.771) |
| CR | 4.337 | 2.353 | 10.559* | 2.513 |
| | (3.317) | (3.835) | (5.668) | (3.148) |
| R&D | .082 | -.127 | .181 | .2** |
| | (.1) | (.135) | (.17) | (.095) |
| PPE | -.638 | 2.459 | 1.079 | -4.385 |
| | (3.294) | (3.802) | (5.577) | (3.126) |
| Duality | -1.547** | -1.033 | -.163 | -1.114* |
| | (.657) | (.795) | (1.127) | (.623) |
| BS | -.573** | -.655** | -.7 | -.349 |
| | (.251) | (.29) | (.429) | (.238) |
| IND | -.113* | -.16** | -.16 | .048 |
| | (.067) | (.076) | (.116) | (.064) |
| _cons | -14.953 | -11.815 | -31.728* | 9.523 |
| | (11.04) | (13.131) | (18.823) | (10.477) |
| Industry FE | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES |
| Observations | 716 | 581 | 695 | 716 |
| R-squared | .227 | .147 | .159 | .106 |

**Panel B:** Growth stage of firm life cycle

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | ESG | E | S | G |
| AI | 1.487*** | 2.287*** | 2.021*** | .261 |
| | (.41) | (.593) | (.59) | (.33) |
| Size | 2.709*** | 2.818*** | 1.957*** | 2.321*** |
| | (.435) | (.654) | (.619) | (.35) |
| Lev | -2.432 | -1.175 | -2.883 | -2.238** |
| | (1.26) | (1.928) | (1.796) | (1.015) |
| Ln(sales) | .619* | 1.043* | 1.273** | -.251 |
| | (.372) | (.558) | (.53) | (.299) |
| Age | 2.44*** | 2.55*** | 3.576*** | -1.121*** |
| | (.474) | (.743) | (.705) | (.382) |
| CR | 1.809 | 1.698 | 1.317 | 3.517*** |
| | (1.526) | (2.332) | (2.185) | (1.229) |
| R&D | .137*** | .21** | .269*** | .058 |
| | (.05) | (.089) | (.072) | (.041) |
| PPE | 2.246 | 3 | -2.132 | 2.035 |
| | (1.612) | (2.239) | (2.284) | (1.298) |
| Duality | -.649* | -.78 | -.862 | -.033 |
| | (.371) | (.558) | (.53) | (.299) |
| BS | -.234* | -.17 | -.235 | -.129 |
| | (.125) | (.179) | (.178) | (.101) |
| IND | .012 | -.015 | -.031 | .007 |
| | (.028) | (.041) | (.04) | (.023) |
| _cons | -60.101*** | -83.552*** | -55.417*** | -.019 |
| | (6.174) | (9.387) | (8.885) | (4.972) |
| Industry FE | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES |
| Observations | 2612 | 2213 | 2559 | 2612 |
| R-squared | .296 | .22 | .215 | .075 |

**Panel C:** Mature stage of firm life cycle

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | ESG | E | S | G |
| AI | .706* | .588 | 1.11** | .94*** |
| | (.369) | (.558) | (.493) | (.305) |
| Size | 2.192*** | 2.408*** | 2.273*** | 1.891*** |
| | (.404) | (.611) | (.546) | (.334) |
| Lev | -3.741*** | -3.056* | -4.69*** | -3.534*** |
| | (1.052) | (1.57) | (1.406) | (.868) |
| Ln(sales) | .416 | .573 | .854* | -.311 |
| | (.363) | (.542) | (.485) | (.3) |
| Age | 3.5*** | 3.7*** | 2.442*** | .626* |
| | (.399) | (.618) | (.55) | (.329) |
| CR | 3.649*** | 6.248*** | -.223 | 6.048*** |
| | (1.15) | (1.79) | (1.558) | (.95) |
| R&D | .045 | .123 | .031 | -.061 |
| | (.049) | (.078) | (.067) | (.041) |
| PPE | -.134 | -2.95 | 1.777 | .256 |
| | (1.347) | (1.947) | (1.781) | (1.112) |
| Duality | .373 | .37 | .223 | .303 |
| | (.293) | (.439) | (.388) | (.242) |
| BS | -.148 | -.226* | -.022 | -.263*** |
| | (.092) | (.131) | (.121) | (.076) |
| IND | -.011 | -.011 | .01 | -.067*** |
| | (.024) | (.034) | (.031) | (.02) |
| _cons | -44.667*** | -63.051*** | -52.587*** | 12.028** |
| | (5.765) | (8.896) | (7.764) | (4.76) |
| Industry FE | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES |
| Observations | 3191 | 2856 | 3134 | 3191 |
| R-squared | .226 | .147 | .134 | .087 |

**Panel D:** Decline stage of firm life cycle

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | ESG | E | S | G |
| AI | .917 | .496 | .603 | 2.43*** |
| | (.638) | (.935) | (.958) | (.539) |
| Size | .501 | .899 | .085 | .763* |
| | (.537) | (.833) | (.818) | (.454) |
| Lev | -3.316** | -2.624 | -2.293 | -2.514** |
| | (1.334) | (2.01) | (2.014) | (1.128) |
| Ln(sales) | .586 | .566 | 1.1* | -.327 |
| | (.407) | (.63) | (.619) | (.344) |
| Age | 3.861*** | 4.65*** | 3.925*** | 1.1** |
| | (.652) | (1.175) | (1.055) | (.551) |
| CR | -.041 | 1.321 | -2.452 | .504 |
| | (1.73) | (2.73) | (2.667) | (1.463) |
| R&D | .095* | .145 | .132 | -.034 |
| | (.054) | (.1) | (.085) | (.046) |
| PPE | 1.194 | 1.497 | .267 | -5.158** |
| | (2.495) | (3.82) | (3.779) | (2.109) |
| Duality | .177 | .419 | .114 | -.04 |
| | (.472) | (.749) | (.732) | (.399) |
| BS | -.142 | .064 | -.442* | -.287* |
| | (.174) | (.272) | (.268) | (.147) |
| IND | -.015 | -.007 | -.072 | .037 |
| | (.036) | (.055) | (.055) | (.031) |
| _cons | -12.139 | -35.87*** | -6.545 | 34.142*** |
| | (8) | (12.424) | (12.314) | (6.763) |
| Industry FE | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES |
| Observations | 1128 | 958 | 1105 | 1128 |
| R-squared | .144 | .099 | .079 | .116 |

**Panel E:** Shakeout stage of firm life cycle

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | ESG | E | S | G |
| AI | 2.004 | 1.609 | 2.583 | 4.731** |
| | (2.766) | (1.816) | (4.019) | (2.229) |
| Size | 1.466 | 10.948 | -11.576 | 2.123 |
| | (6.448) | (6.525) | (9.627) | (5.195) |
| Lev | -1.383 | 5.772 | -15.036 | 2.022 |
| | (9.878) | (8.043) | (14.568) | (7.958) |
| Ln(sales) | -1.423 | -8.87* | 8.398 | -6.007 |
| | (5.896) | (4.762) | (8.569) | (4.75) |
| Age | 4.466 | -8.946 | 8.322 | -.283 |
| | (4.773) | (5.188) | (7.019) | (3.845) |
| CR | 13.857* | -16.589* | 16.646 | 25.497*** |
| | (7.356) | (7.991) | (11.004) | (5.927) |
| R&D | -.269 | -.223 | .047 | -.277 |
| | (.299) | (.204) | (.438) | (.241) |
| PPE | -4.062 | 47.83 | -1.329 | -24.557 |
| | (21.118) | (30.598) | (30.681) | (17.015) |
| Duality | 1.511 | -5.896 | .608 | 3.54** |
| | (1.818) | (3.626) | (2.68) | (1.464) |
| BS | 2.012 | -2.259 | 5.015 | -.545 |
| | (6.058) | (6.175) | (8.8) | (4.881) |
| IND | .511 | -.919 | .76 | .553 |
| | (1.298) | (1.353) | (1.886) | (1.046) |
| _cons | -30.225 | 26.801 | 8.861 | 11.662 |
| | (121.085) | (103.506) | (182.92) | (97.556) |
| Industry FE | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES |
| Observations | 155 | 129 | 149 | 155 |
| R-squared | .306 | .502 | .337 | .68 |

***Note**: Standard errors are shown in parentheses, with significance levels indicated as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.*

Moreover, the results in column (7) shows that ROA has statistically significant coefficient of 1.475 with ESG at the 10 % level. Because using AI-driven technology will help companies maximize operational efficiency, increase decision-making, and stimulate innovation, therefore producing better strategic and financial results (Bosse *et al.*, 2023). By means of automation and predictive analytics, artificial intelligence helps companies to simplify procedures, save costs, and improve output. These findings strongly suggest that the integration of AI in heightened firm performance, subsequently enhancing firm ESG performance. The results aligns with prior research (Hou *et al.*, 2024), highlighting the crucial role of improved firm performance, as measured by ROA, in facilitating the connection between AI and ESG.

*Alternative Variable Using WIND-ESG Score*

Various agencies employ diverse criteria to assess corporate ESG performance, potentially introducing "noise" into research conclusions. To address ESG decoupling resulting from multiple ratings, the ordinary least squares approach for robustness testing was applied using WIND ESG scores. The regression results with WIND ESG scores substituted are displayed in column (1) of table 8, showing a 5% significance level with ESG coefficient of 0.266. Even after using alternative variable method, the considerable positive impact of AI on corporate ESG performance persists, underscoring the research's reliability. Furthermore, examining the impact of AI on ESG performance through the lens of FLCS using WIND ESG scores revealed consistent and significant resul.

Table 8

**Alternative Variable using WIND-ESG Score**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | ESG_Wind | Intro-FLCS | Gro-FLCS | Mat-FLCS | Dec-FLCS | Shake-FLCS |
| AI | .266** | .072 | .571* | .26** | .137 | -.766 |
| | (.122) | (.43) | (.295) | (.326) | (.026) | (.559) |
| Size | .217 | .513 | .006 | -.354 | -.73 | .621 |
| | (.134) | (.579) | (.335) | (.453) | (2.601) | (.564) |
| Lev | -.142 | 1.725 | -.56 | .325 | -16.723 | .952 |
| | (.295) | (1.228) | (.54) | (1.338) | (11.453) | (1.421) |
| Ln(sales) | -.14 | -.282 | .017 | .041 | -.529 | .025 |
| | (.114) | (.404) | (.274) | (.338) | (2.795) | (.513) |
| Age | -.37*** | -.266 | -.149 | .378 | -4.485 | -1.472*** |
| | (.099) | (.43) | (.254) | (.353) | (3.442) | (.504) |
| CR | -.426 | -.927 | -.057 | -.691 | -10.534 | -1.185 |

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | ESG_Wind | Intro-FLCS | Gro-FLCS | Mat-FLCS | Dec-FLCS | Shake-FLCS |
| | (.29) | (1.194) | (.715) | (.898) | (6.506) | (1.266) |
| R&D | -.041*** | -.03 | -.049* | -.062** | .06 | -.069** |
| | (.01) | (.061) | (.025) | (.03) | (.222) | (.032) |
| PPE | .398 | .147 | .173 | -1.533 | .186 | -1.855 |
| | (.424) | (1.705) | (.852) | (1.277) | (6.259) | (1.96) |
| Duality | -.15 | -.033 | -.271 | -.645** | -376 | -.199 |
| | (.097) | (.37) | (.244) | (.28) | (.183) | (.333) |
| BS | .044 | .172 | -.085 | .09 | .868 | -.153 |
| | (.041) | (.175) | (.078) | (.103) | (.6) | (.219) |
| IND | .011 | .039 | -.003 | .031 | .023 | .035 |
| | (.009) | (.034) | (.022) | (.027) | (.013) | (.026) |
| _cons | -7.813*** | -14.178 | -5.053 | -1.173 | 25.971 | -16.233* |
| | (2.301) | (10.628) | (5.243) | (7.795) | (38.49) | (8.568) |
| Industry FE | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES |
| Observations | 3659 | 675 | 1262 | 1210 | 171 | 341 |
| R-squared | .025 | .065 | .036 | .045 | .825 | .216 |

*Note: Standard errors are shown in parentheses, with significance levels indicated as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.*

**Heterogeneity Analysis**

*SOEs vs Non-SOEs*

In economies such as China's, where the government holds significant stakes in firms' ownership tends to be concentrated. We delved into the relationship between AI and ESG factors, examining both SOEs and non-SOEs. Our analysis, detailed in table 9, panel A, columns (1-4), indicates that AI technology does not substantially alter ESG performance or its components within SOEs. Conversely, non-SOEs demonstrate a marked enhancement in ESG performance by integrating AI, evidenced by a statistically positive effect at the 10 % significance level (columns 5-8 of panel A). These findings underscore that AI positively influences ESG performance exclusively in non-SOEs, with no discernible impact observed in SOEs. Numerous studies suggest that Chinese non-SOEs place a higher priority on corporate governance, social responsibility and environmental sustainability compared to SOEs (Hussain *et al.*, 2024; Q. J. Wang *et al.*, 2023). This differentiation is attributed to the bureaucratic ties and slower decision-making processes inherent in SOEs due to government involvement. The diverse range of factors affecting the ESG performance of non-SOEs means that they are less influenced by single factors compared to other types of activities. This contributes to the difference or divergence observed between non-SOEs and other entities. In addition, non-SOEs are under more investor scrutiny and market competitiveness, which motivates them to use AI-driven ESG approaches to improve sustainability, efficiency and openness. By contrast, SOEs could rely more on government support and regulatory compliance than on proactive ESG programs.

*High vs Low Bank Concentration*

An in-depth examination of the impact of AI on ESG performance reveals nuanced distinctions between regions with low and high bank concentration. First, in regions with fewer banks, firms enjoy greater flexibility in investing in AI initiatives aimed at enhancing ESG metrics, leveraging a broader spectrum of funding sources beyond traditional banking channels (Fernandez & Wigger, 2016). Conversely, enterprises operating in areas with high bank concentration may encounter challenges in securing loans and might exhibit reduced motivation to engage in AI-driven ESG initiatives. Second, limited banking resources and more borrowing costs in low bank concentration areas might cause enterprises to have more financing restrictions. This motivates them to implement AI-driven ESG plans in order to draw institutional investors and ESG-oriented funds, hence attracting other financing sources (Long et al., 2023). These companies are more desirable to investors that give sustainability and governance criteria top priority as artificial intelligence helps them to increase transparency, maximize resource allocation, and improve ESG reporting.

On the other hand, companies have less need to incorporate AI for ESG enhancements in high bank concentration areas as they have simpler access to conventional finance. Companies are less under pressure to use AI for sustainability reporting or governance improvements since banks in these areas could give financial stability top priority over ESG factors. Furthermore, the existence of strong banks can create a less competitive market, therefore lowering companies' incentives to stand out with ESG initiatives backed by artificial intelligence.

This phenomenon potentially constrains the extent to which AI can shape ESG performance. By segmenting the data based on bank concentration levels enabled us to scrutinize this relationship effectively. Specifically, we denote the number of bank branches per capita in province c in year $_{t-1}$ as Bank $_{c,t-1}$. Our analysis reveals compelling evidence in support of the notion that regions with lower bank concentration exhibit a more pronounced and statistically significant relationship between AI and its impact on ESG metrics, as evidenced by the results in columns 5-8 of table 9, panel C as compared to high bank concentrated regions. This finding underscores the notion that lower bank concentration environments facilitate easier access for businesses to harness the advantages of AI, consequently yielding superior ESG outcomes.

Table 7

**Mechanism Analysis**

| | Green innovation | | | | | Firm performance | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| | GI | ESG | E | S | G | ROA | ESG | E | S | G |
| AI | .032** | .978*** | 1.051*** | 1.453*** | .871*** | .01*** | 1.018*** | 1.101*** | 1.457*** | .89*** |
| | (.016) | (.202) | (.296) | (.284) | (.162) | (.003) | (.202) | (.297) | (.284) | (.162) |
| GI | | .421*** | .61*** | .355*** | .215*** | | | | | |
| | | (.077) | (.11) | (.109) | (.062) | | | | | |
| ROA | | | | | | | 1.475* | 1.124 | .944 | 2.109*** |
| | | | | | | | (.802) | (1.203) | (1.121) | (.643) |
| All control variables | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| _cons | -2.177*** | -38.993*** | -55.323*** | -47.492*** | 19.181*** | .295*** | -40.574*** | -57.721*** | -49.023*** | 17.865*** |
| | (.208) | (2.782) | (4.369) | (3.947) | (2.234) | (.046) | (2.799) | (4.385) | (3.964) | (2.244) |
| Industry FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 23540 | 7796 | 6734 | 7640 | 7796 | 23984 | 7802 | 6737 | 7642 | 7802 |
| R-squared | .036 | .238 | .15 | .154 | .068 | .092 | .238 | .149 | .153 | .067 |

*Note: Standard errors are shown in parentheses, with significance levels indicated as follows: *** p < 0.01, ** p < 0.05, * p < 0.1. Moreover, results of control variables are not reported due to brevity.*

Table 9

**Heterogeneity Analysis**

| Panel B: Bank concertation | High Bank concertation | | | | Low Bank concertation | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | ESG | E | S | G | ESG | E | S | G |
| AI | -.456 | -.526 | .436 | -.283 | .732** | .968** | 1.333*** | -.018 |
| | (.297) | (.46) | (.417) | (.212) | (.29) | (.406) | (.424) | (.227) |
| All control variables | YES | YES | YES | YES | YES | YES | YES | YES |
| _cons | -29.271*** | -41.616*** | -37.838*** | 33.535*** | -14.943** | -14.485 | -45.191*** | 45.446*** |
| | (5.035) | (8.519) | (7.108) | (3.599) | (6.715) | (9.233) | (9.765) | (5.247) |
| Industry FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 3584 | 3023 | 3498 | 3584 | 4114 | 3612 | 4040 | 4114 |
| R-squared | .32 | .246 | .185 | .234 | .281 | .191 | .194 | .251 |

*Note: Standard errors are shown in parentheses, with significance levels indicated as follows: *** p < 0.01, ** p < 0.05, * p < 0.1.*

**Endogeneity Analysis**

*Propensity Score Matching (PSM)*

In order to address the potential concerns regarding functional misspecification, this study employs PSM, a robust technique aimed at bolstering the validity of study findings. This method effectively addresses these concerns by establishing comparable characteristics between treated and control groups, thereby constructing a mirrored control group. This process involves integrating predetermined control factors as matching variables. Specifically, we adopted the approach of (Hussain *et al.*, 2024; Yang *et al.*, 2024), and assign the treatment group firms that have adopted AI technology, while the control group consists of those that have not adopted AI technology. Drawing from these AI studies, we employ a one-to-one closest neighbor matching approach alongside a selection of control variables to identify a control group closely resembling the treatment group.

To ensure the reliability of our analysis, we initially visualize the distribution of these characteristics before and after the matching process in figure 2. This visual examination allows us to discern any discrepancies pre- and post-treatment. Subsequently, in figure 2(a), we employ the kernel matching method to align the groups based on their characteristics, validating the common support assumption. This involves estimating the probability density of characteristics for each group using a kernel function and matching them based on similar probability densities. This step ensures comparability between the treatment and control groups, thereby minimizing bias in estimating treatment effects. Following this, we reassess equation (1) using data from the matched sample. The results of the matched sample are presented in table 10, panel A, while panel B shows the regression results of PSM across columns 1-4. Notably, the coefficients obtained for AI adoption with ESG and its subcomponents are positive and statistically significant at the 1% level, particularly with regard to overall ESG performance. This outcome reaffirms the reliability of our initial benchmark findings.

Table 10

**Propensity Score Matching**

| **Panel A:** Match sample | Mean | | t-test | | | V(T)/ |
|---|---|---|---|---|---|---|
| Variable | Treated | Control | %bias | t | p>t | V(C) |
| Size | 23.115 | 23.144 | -2.300 | -.770 | .443 | .87* |
| Lev | .454 | .447 | 3.7 | 1.230 | .218 | .76* |
| Ln(sales) | 22.496 | 22.468 | 1.9 | .640 | .524 | .82* |
| Age | 2.521 | 2.508 | 2.3 | .770 | .439 | .85* |
| CR | .166 | .168 | -2.100 | -.700 | .484 | .92* |
| R&D | 5.626 | 5.649 | -.500 | -.140 | .891 | .86* |
| PPE | .177 | .174 | 1.5 | .580 | .559 | 1.060 |
| Duality | .244 | .266 | -5.300 | -1.730 | .083 | .12 |
| BS | 8.899 | 8.838 | 3.3 | 1.130 | .260 | 1.020 |
| IND | 37.666 | 37.866 | -3.500 | -1.180 | .238 | .83* |

| **Panel B:** PSM regression | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | ESG | E | S | G |
| AI | .909*** | 1.094** | .485 | .816*** |
| | (.312) | (.463) | (.472) | (.242) |
| Size | 1.826*** | 1.84*** | 1.524*** | 1.759*** |
| | (.308) | (.487) | (.46) | (.239) |
| Lev | -2.956*** | -3.463*** | -4.598*** | -2.548*** |
| | (.832) | (1.302) | (1.218) | (.645) |
| Ln(sales) | .664** | 1.063** | .816** | -.174 |
| | (.265) | (.416) | (.387) | (.205) |
| Age | 3.14*** | 3.739*** | .619 | .01 |
| | (.338) | (.532) | (.73) | (.262) |
| CR | 1.612* | .949 | -.683 | 3.686*** |
| | (.934) | (1.465) | (1.365) | (.724) |
| R&D | .108*** | .122** | .133*** | .002 |
| | (.03) | (.053) | (.044) | (.023) |
| PPE | .162 | .733 | -.062 | -1.723* |
| | (1.304) | (1.907) | (1.87) | (1.011) |
| Duality | -.123 | .335 | -.262 | -.126 |
| | (.242) | (.376) | (.348) | (.187) |
| BS | -.099 | -.131 | -.008 | -.163*** |
| | (.08) | (.118) | (.116) | (.062) |
| IND | 0 | -.024 | -.004 | .008 |
| | (.02) | (.031) | (.029) | (.016) |
| _cons | -42.96*** | -62.618*** | -32.513*** | 9.6*** |
| | (4.309) | (6.867) | (6.924) | (3.342) |
| Industry FE | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES |

| **Panel B:** PSM regression | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | ESG | E | S | G |
| Observations | 3900 | 3363 | 3854 | 3900 |
| R-squared | .234 | .162 | .158 | .085 |

***Note**: Standard errors are shown in parentheses, with significance levels indicated as follows: *** p < 0.01, ** p < 0.05, * p < 0.1.*

*Two-Stage Least Square*

The potential endogeneity issues arising from reverse causality raise concerns regarding the accuracy of the study's primary findings. For instance, firms aiming to enhance their ESG performance may exhibit greater activity in implementing AI projects, leading to biased results. To mitigate this, we employ a two-stage least squares (2SLS) estimation to reevaluate the underlying regression model. By following Hussain et al. (2024), we select a suitable instrument variable (IV) to measure industry-level AI adoption technology (AI_IV). This IV is determined as the industry-year mean of AI keyword frequencies using 3-digit industry codes. By considering AI trends at the industry level, which are less likely to be influenced by individual firm decisions. The results of the IV regression, presented in panel A of table 11, demonstrate a positive and statistically significant association at 1% level between the AI_IV at the industry level and AI at the firm level from column 1-4, confirming the validity of the instrument. Furthermore, the results in panel B, shows that AI has a positive and statistically significant coefficients with ESG performance and its subcomponents except social, indicating that the positive correlation between ESG and AI persists even after addressing potential endogeneity through instrumental variable analysis.

Table 11

**Two-Stage Least Square**

| Panel A: First stage | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Variables | AI | AI | AI | AI |
| AI_IV | .816*** | .834*** | .818*** | .816*** |
| | (.027) | (.031) | (.028) | (.027) |
| All control variables | YES | YES | YES | YES |
| _cons | -.256** | -.237** | -.248** | -.256** |
| | (.103) | (.110) | (.105) | (.103) |
| Industry FE | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES |
| Observations | 7,802 | 7,802 | 7,802 | 7,802 |
| R-squared | .222 | .208 | .220 | .222 |

| Panel B: Second stage | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | ESG | E | S | G |
| AI | 1.302*** | 1.148** | 1.122 | .266*** |
| | (.515) | (.703) | (.766) | (.387) |
| All control variables | YES | YES | YES | YES |
| _cons | -36.733*** | -50.918*** | -38.081*** | 7.628*** |
| | (1.584) | (2.035) | (2.345) | (1.190) |
| Industry FE | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES |
| Observations | 7,802 | 7,802 | 7,802 | 7,802 |
| R-squared | .251 | .196 | .131 | .214 |

***Note**: Standard errors are shown in parentheses, with significance levels indicated as follows: *** p < 0.01, ** p < 0.05, * p < 0.1.*

## Conclusion and Policy Implications

*Conclusion*

The increasing impact of the AI on global sphere highlights the necessity of examining how firms have adapted in the era of technological advancement. With a heightened awareness of ESG issues globally and among Chinese landscape, urge the academia to determine the factors that drives and solve ESG related issues. Drawing from literature on AI and RBV theory, this study investigates the repercussions of AI technology on ESG and its various aspects. The analysis focuses on Chinese A-share listed firms spanning from 2010 to 2020, culminating with a final firm year observation 10,821. Firstly, the primary findings of the study reveal that AI significantly enhances ESG performance, emphasizing the pivotal role of technological advancement in fostering sustainable and social practices. Secondly, this study checks the AI impact on ESG performance through FLCS perspective and the examination across various stages of the FLCS reveals distinct patterns. Notably, firms in the growth and maturity stages actively engage in AI and ESG activities, while those in the introductory, decline and shakeout stages show no significant impact on this relationship. Thirdly, this research adopts a dual-channel approach to elucidate how AI contributes to the enhancement of firms ESG performance. On one side, through the GI channel, AI strengthens a firm's GI, thereby augmenting its overall

ESG performance. On the other side, via the firm performance channel, AI positively impacts a firm overall performance, consequently bolstering its ESG performance as well.

The study also examines the heterogeneity effect across various scenarios to gain a deeper understanding of the relationship between AI and ESG performance. The findings reveal that the positive effect of AI on ESG performance is more pronounced for non-SOEs compared to SOEs. This suggests that non-SOEs may be more agile and adaptable in integrating AI technologies into their operations, leading to more significant improvements in ESG outcomes. While, the study finds that firms located in regions with lower bank concentration exhibit a stronger positive relationship between AI and ESG performance. This indicates that in regions with less concentrated banking sectors, firms may have more autonomy and flexibility to prioritize ESG initiatives and invest in AI technologies to drive sustainable practices. Lastly, the study's findings demonstrate robustness and consistency across multiple statistical approaches, encompassing 2SLS and PSM methods. These methodological robustness checks instill confidence in the reliability and validity of our results, strengthening the credibility of our study outcomes.

*Policy Implication, Future Research and Limitation*

The study's conclusions offer valuable insights for policymakers, government officials, and firms management, providing a roadmap for leveraging AI to enhance ESG practices and drive sustainable development. First and foremost, policymakers and government entities play a pivotal role in encouraging and facilitating the integration of AI technologies within firms. This can be achieved through strategic financing and subsidies for AI research and development, incentivizing firms to adopt cutting-edge technologies. Additionally, to catalyze improvements in ESG performance and environmental sustainability, policymakers should enact regulations and laws that create a supportive framework for the adoption of AI technology. Moreover, ensuring that ESG practices effectively utilize AI capabilities requires investments in educational and training programs. By funding initiatives that equip individuals with the requisite skills to harness AI for sustainability purposes, policymakers can cultivate a skilled workforce capable of driving meaningful change. On the organizational front, firm managers hold the responsibility to embrace and invest in AI technology to bolster ESG performance. Allocating resources and budgets for AI initiatives and fostering collaboration with technology suppliers and researchers are integral components of this strategy. Ultimately, to maximize the impact of AI on ESG performance and sustainable development, it is imperative for governments, legislators, and corporate management to consider the real-world consequences of their actions. By aligning strategies and objectives with broader societal and environmental goals, stakeholders can collectively drive positive change and create a more sustainable future. Our study has limitations and offers prospects for future research. As the first to explore the relationship between AI and firms ESG performance, it acknowledges its constraints and guides future investigations. Firstly, despite robustness checks, our analysis is limited to Chinese A-share listed firms, potentially restricting generalizability. Future research could replicate our findings in other emerging nations to offer a broader examination across diverse sectors. Secondly, our methodology to measure AI, using CATA in the MD&A sections of annual reports, poses challenges. As firms may shape public perceptions with positive narratives. Future studies should explore alternative AI measurement methods to enhance reliability and provide deeper insights into this nexus.

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