

Article

Digital Economies and Artificial Intelligence: Unlocking Eco-Innovation in Asian Firms

Marwan Mansour ^{1,*}, Ismail Younes Yamin ¹, Abdulrahman Alomair ^{2,*} and Mohammed Alomair ²¹ Faculty of Business, Amman Arab University, Amman 11953, Jordan; i.yamin@aau.edu.jo² Accounting Department, Business School, King Faisal University, Al-Ahsa 31982, Saudi Arabia; momair@kfu.edu.sa

* Correspondence: m.mansour@aau.edu.jo (M.M.); aamalomair@kfu.edu.sa (A.A.)

Abstract

Artificial intelligence (AI) is increasingly transforming firms' innovation processes and creating new opportunities for sustainable development; however, empirical evidence on how firm-level AI capability influences eco-innovation under different digital environments remains limited. Drawing on the Natural Resource-Based View and Dynamic Capability Theory, this study examines the effect of AI capability on firm-level eco-innovation and investigates whether national digital economy development strengthens this relationship. The analysis uses an unbalanced panel of 5564 listed firms from 15 Asian economies over the period 2017–2024. Firm fixed-effects models are employed as the primary estimation approach, while moderation analysis is complemented by System GMM, propensity score matching, and Heckman two-step estimation to address potential endogeneity and sample-selection concerns. AI capability is measured using a disclosure-based index derived from textual analysis of firms' annual and sustainability reports. The results indicate that AI capability is positively associated with eco-innovation and that this relationship is significantly stronger in countries with more advanced digital economies. These findings suggest that supportive digital ecosystems enhance firms' ability to convert AI capability into sustainable innovation outcomes. The study contributes to the literature by demonstrating that national digital economy development serves as an important contextual condition shaping the effectiveness of firm-level AI capability in promoting eco-innovation.

Keywords: artificial intelligence; digital economy; eco-innovation; green innovation; digital transformation; sustainable development; Asian economies

1. Introduction

Sustainable development has become a central concern for governments, firms, and international institutions. Industrialization, environmental degradation, and climate change have intensified the need for innovative approaches that balance economic development with environmental sustainability [1]. This challenge is particularly important in many Asian economies, where rapid economic growth, rising energy demand, environmental vulnerability, and accelerating digital transformation occur simultaneously [2]. In recent years, many Asian countries have actively promoted AI, digital transformation, and green development as complementary pillars of long-term economic growth, making the region an ideal setting for examining how AI-enabled innovation contributes to sustainable development across diverse institutional and technological environments Xu and Lin [3], Liu, Shen [4], Mijit, Hu [5]. Consequently, governments and international organizations increasingly



Academic Editor: Zudi Lu

Received: 17 June 2026

Revised: 18 July 2026

Accepted: 26 July 2026

Published: 28 July 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

recognize technological innovation as a key driver of sustainable development. Within this context, eco-innovation—encompassing environmentally friendly products, production processes, and managerial practices—has become an essential mechanism through which firms improve environmental performance while maintaining long-term competitiveness.

However, the environmental implications of digital transformation are becoming increasingly complex. The information and communications technology (ICT) sector is estimated to account for approximately 2–4% of global greenhouse gas emissions, while global data centre electricity consumption reached nearly 460 TWh in 2022 owing to the rapid expansion of cloud computing, AI, and digital infrastructure [6]. These developments illustrate that digital technologies simultaneously create opportunities for sustainable innovation while increasing pressure to improve the environmental efficiency of digital transformation. Consequently, firms are increasingly expected to integrate digital technologies with sustainability strategies to generate both economic and environmental value [7].

Meanwhile, breakthroughs in AI are fundamentally transforming production systems and business processes [8,9]. AI enables firms to process large volumes of data, automate routine operations, optimize resource allocation, and improve strategic decision-making, thereby enhancing energy efficiency, emissions monitoring, supply-chain management, and sustainable product design through data-driven decision-making and greater operational transparency [10]. Recent empirical evidence demonstrates that AI significantly enhances firms' green innovation capability by strengthening organizational learning, improving R&D productivity, accelerating knowledge creation, and increasing operational efficiency [11–13]. More recent studies further show that AI functions as a general-purpose technology capable of improving environmental performance by facilitating intelligent resource allocation, supporting green technological innovation, and enhancing firms' adaptive capabilities in rapidly changing business environments [4,14–16]. Accordingly, AI has become an important driver of digital economic transformation, innovation performance, and sustainable competitiveness [3,17,18]. AI also enables firms to integrate environmental information into strategic decision-making, thereby improving both the quality and efficiency of eco-innovation [3,11].

Nevertheless, AI adoption alone does not automatically generate environmental benefits. Increasing evidence suggests that the effectiveness of AI depends on complementary organizational capabilities, digital infrastructure, institutional support, and implementation readiness that enable firms to successfully transform technological capability into sustainable innovation [14,19,20]. This argument is also consistent with [21], who demonstrate that AI implementation enhances organizational performance only when supported by complementary organizational resources and effective implementation readiness. Together, these studies indicate that AI creates value not merely through technological adoption itself, but through the interaction between firm capabilities and the broader digital environment, providing a strong theoretical rationale for examining the moderating role of digital economy development.

Against this background, digital economy development has emerged as a critical factor shaping firms' ability to exploit AI for sustainable innovation. Digital economy development reflects the availability of digital infrastructure, data resources, connectivity, technological ecosystems, and institutional support that facilitate firms' digital transformation. Countries with more advanced digital economies provide stronger innovation networks, richer data resources, greater knowledge spillovers, and more supportive institutional environments that enable firms to translate AI capability into eco-innovation more effectively [22,23]. Conversely, firms operating within weaker digital ecosystems may struggle to exploit AI technologies because of inadequate digital infrastructure, fragmented data resources, and weaker institutional support. Consequently, digital economy development is

expected to function as an important boundary condition that amplifies the effectiveness of firm-level AI capability by facilitating knowledge diffusion, improving resource allocation, reducing information asymmetry, and accelerating digital transformation [20,24].

Although research on AI, digital transformation, and sustainability has expanded considerably in recent years, three important research gaps remain. First, the available empirical evidence is largely confined to single-country settings—particularly China—limiting our understanding of whether the relationship between AI capability and eco-innovation generalizes across different institutional, technological, and digital development contexts [3,25]. Recent studies continue to focus predominantly on Chinese firms despite recognizing that institutional quality, technological readiness, and digital maturity substantially influence AI-driven innovation outcomes [4,15,16]. Asia represents a highly heterogeneous region with respect to digital economy development, AI governance, technological readiness, and environmental regulation [26]. This diversity provides a unique empirical setting for investigating how national digital ecosystems influence firms' ability to transform AI capability into eco-innovation across heterogeneous institutional environments [20,26,27].

Second, although previous studies have examined the independent effects of AI capability or digitalization on green innovation, considerably less attention has been devoted to understanding how country-level digital economy development strengthens or constrains the effectiveness of firm-level AI capability in generating eco-innovation [20,28–31].

Third, despite growing evidence that AI capability and digital economy development independently promote sustainable innovation, limited research has adopted a multilevel perspective that simultaneously integrates firm-level technological capability with country-level digital economy development to explain eco-innovation across multiple institutional settings. Addressing this gap is particularly important because firms' technological capabilities are embedded within broader national digital environments that may either facilitate or constrain the successful translation of AI capability into sustainable innovation.

To fill these gaps, this study examines the relationship between AI capability and corporate eco-innovation and investigates whether digital economy development moderates this relationship across Asian economies. The study draws upon the NRBV and DCT to explain how firms transform AI capability into sustainable innovation. From the NRBV perspective, AI represents a valuable strategic resource that enables firms to identify environmental opportunities, improve resource efficiency, and develop environmentally sustainable products and processes. DCT complements this perspective by explaining how firms continuously integrate, reconfigure, and leverage AI-enabled resources to respond to rapidly changing technological and environmental conditions. Accordingly, firms operating in more advanced digital economies are expected to exploit AI capability more effectively because supportive digital ecosystems provide complementary infrastructure, knowledge networks, institutional support, and technological resources that facilitate eco-innovation.

The empirical analysis employs a large multi-country panel of publicly listed firms across Asian economies during 2017–2024. To ensure the robustness of the findings and address potential endogeneity concerns, the study employs firm fixed-effects estimation together with several complementary approaches, including System Generalized Method of Moments (System GMM), PSM, and the Heckman two-step selection model. The findings indicate that AI capability significantly enhances corporate eco-innovation and that this positive relationship becomes substantially stronger in countries with more developed digital economies.

The contributions of this study are threefold. First, it provides one of the few cross-country empirical investigations of the relationship between firm-level AI capability and eco-innovation among Asian listed firms, extending the predominantly China-based literature and improving the generalizability of existing evidence. Second, it demonstrates

that country-level digital economy development constitutes an important boundary condition that strengthens the translation of firms' AI capability into eco-innovation, thereby providing new evidence on how national digital ecosystems shape firm-level sustainability outcomes. Third, by integrating the NRBV and DCT, the study develops a multilevel theoretical framework linking firm-level technological capabilities with country-level digital ecosystems. This multilevel perspective advances the literature on AI, digital transformation, and sustainable innovation by explaining how interactions between organizational capabilities and national digital environments jointly influence eco-innovation across heterogeneous institutional settings.

2. Literature Review and Hypothesis Development

2.1. AI and Corporate Eco-Innovation

The digital transformation process has changed the way firms gain competitiveness and sustainability. AI is one of the emerging technologies playing a key role in firm and industry transformation [18,25]. AI capability refers to a firm's ability to acquire, integrate, deploy, and leverage AI technologies, data resources, and analytical expertise to improve organizational decision-making, operational efficiency, and innovation performance. AI helps firms in various industries, including manufacturing, finance, and energy, analyze large amounts of information, automate processes, and improve decision-making [12,32]. This enhances efficiency, minimizes wastage, and facilitates the creation of eco-friendly products and processes. As a result, AI is increasingly recognized as a technology facilitating corporate eco-innovation [33]. Moreover, the recent literature defines AI as a general-purpose technology that has the potential to boost innovation and drive production system transformation in various industries [18]. Recent studies further suggest that AI enhances organizational learning, knowledge integration, and resource optimization, enabling firms to accelerate environmentally sustainable innovation and improve long-term competitiveness [4,14,16].

Eco-innovation is the creation of products, processes, or organizational practices that improve environmental performance without impairing (or even enhancing) economic performance. Eco-innovation differs from traditional innovation by explicitly incorporating environmental objectives into the development of technologies and production systems, encouraging firms to improve resource efficiency, reduce emissions, and pursue sustainable production [11,34]. This often requires firms to process complex environmental information, integrate diverse technological knowledge, and continuously optimize production systems, capabilities that AI substantially strengthens through advanced analytics, machine learning, and intelligent decision-support systems [15,32].

The NRBV and DCT perspectives provide a strong theoretical foundation for explaining the relationship between AI capability and eco-innovation. According to the NRBV, firms achieve sustainable competitive advantage by developing strategic resources and capabilities that simultaneously generate environmental and economic value [35]. AI aligns with this perspective because data analytics and machine learning enable firms to monitor environmental performance, identify operational inefficiencies, optimize resource utilization, and reduce environmental impacts. The DCT complements the NRBV by emphasizing firms' ability to sense environmental changes, seize emerging opportunities, and continuously reconfigure organizational resources in response to dynamic technological and regulatory conditions. Environmentally sustainable production therefore requires firms to continuously adapt their technological capabilities to evolving environmental regulations, market expectations, and stakeholder demands.

AI technologies strengthen these dynamic capabilities by enhancing environmental sensing, opportunity recognition, knowledge integration, and resource reconfiguration

through intelligent production systems [14]. Collectively, the NRBV explains why AI represents a valuable strategic environmental resource, whereas DCT explains how firms continuously leverage and reconfigure AI-enabled capabilities to generate sustainable innovation under changing environmental conditions. Together, these theories suggest that AI capability improves firms' ability to transform environmental knowledge into eco-innovation.

Emerging empirical evidence supports the role of AI in promoting green innovation. Research shows that AI technologies improve knowledge integration, technological experimentation, resource efficiency, and environmental productivity, thereby facilitating eco-innovation [5,23,36,37]. Furthermore, AI contributes to higher-quality innovation and more efficient production processes that improve firms' environmental performance [29,38,39]. Companies adopting AI technologies also demonstrate stronger innovation capability and superior knowledge discovery [18]. Moreover, AI and complementary digital technologies, such as blockchain, improve supply-chain coordination, increase information transparency, and reduce environmental externalities through real-time data sharing and more efficient resource utilization [10].

Nevertheless, existing evidence also suggests that AI implementation alone does not automatically generate sustainable innovation outcomes. Recent studies emphasize that firms require complementary organizational capabilities, implementation readiness, supportive digital infrastructure, and favorable institutional conditions to fully exploit AI technologies [20,21]. Consequently, the environmental benefits of AI depend not only on technological capability itself but also on firms' ability to integrate AI within supportive organizational and digital ecosystems.

However, empirical findings remain mixed. Ref. [25] report that the effects of AI on green technological innovation vary across institutional and regulatory environments. Similarly, differences in digital ecosystem development and technological readiness influence firms' ability to convert AI capability into eco-innovation [26,40]. Recent evidence further indicates that firms operating in more advanced digital economies benefit from superior digital infrastructure, richer data resources, stronger knowledge spillovers, and more supportive institutional environments, enabling them to utilize AI more effectively for sustainable innovation [20,29,30,38].

Taken together, these theoretical and empirical arguments suggest that AI capability enhances firms' ability to acquire, process, and apply environmental knowledge, improve resource efficiency, and develop environmentally sustainable products and processes. Although the magnitude of these benefits may depend on organizational and contextual conditions, the overall evidence consistently indicates that firms possessing stronger AI capability are more likely to achieve superior eco-innovation performance. Accordingly, the following hypothesis is proposed:

H1. *AI capability is positively associated with firms' eco-innovation.*

2.2. Digital Economy Development as a Moderating Context

AI offers firms advanced technological capabilities, but the extent to which these capabilities translate into eco-innovation depends on the quality of the digital environment in which firms operate. A digital economy is characterized by digital infrastructure, connectivity, data resources, and the widespread adoption of digital technologies that facilitate innovation, productivity, and sustainable development [40]. Advanced digital economies reduce information asymmetry, improve digital connectivity, strengthen data ecosystems, and enhance knowledge diffusion, thereby creating favorable conditions for firms to adopt and exploit AI technologies more effectively [7,31,41]. Consequently, countries with more developed digital economies provide firms with stronger techno-

logical resources, innovation complementarities, and institutional support that facilitate AI-enabled innovation [15,42,43].

Specifically, digital economies provide firms with access to high-quality data resources, cloud computing, digital platforms, and interconnected innovation networks that facilitate the integration of AI into business operations and innovation activities [34]. Recent studies confirm that AI-driven innovation depends on the availability of digital infrastructure and data ecosystems that enable firms to transform AI capability into innovation productivity [18]. Recent evidence further demonstrates that firms operating within digitally advanced ecosystems benefit from richer data resources, stronger knowledge spillovers, and more supportive institutional environments, enabling AI capability to generate greater innovation productivity and eco-innovation outcomes [4,14]. Moreover, AI implementation generates superior organizational value when supported by complementary digital resources, implementation readiness, and knowledge-sharing capabilities, highlighting the importance of external digital environments in maximizing the benefits of AI technologies [21,37].

Recent systematic reviews further emphasize the growing importance of AI within digital economies. Ref. [17] reviewed 36 studies published between 2021 and 2025 and concluded that AI enhances automation, productivity, decision-making, digital business models, and organizational innovation across industries. Collectively, these findings indicate that AI does not operate in isolation; rather, its innovation benefits depend on supportive digital ecosystems that facilitate the effective deployment, integration, and utilization of AI technologies.

The moderating role of digital economy development is supported by Institutional Theory and the National Innovation Systems (NIS) perspective. Institutional Theory argues that firms' strategic decisions and capability development are shaped by formal institutions, regulatory quality, governance structures, and supporting infrastructure that provide legitimacy, incentives, and access to critical resources [44]. Consequently, firms operating in digitally advanced economies benefit from stronger digital governance, higher-quality infrastructure, and more efficient digital markets that reduce technology adoption costs and facilitate knowledge diffusion [45,46]. Complementing this perspective, the National Innovation Systems approach emphasizes that country-level technological readiness, absorptive capacity, collaborative innovation networks, and digital capabilities strengthen firms' innovation performance by promoting learning, knowledge spillovers, and technological complementarities [14,27]. Together, these perspectives suggest that digital economy development functions as an enabling institutional environment that strengthens firms' ability to exploit AI capability for sustainable innovation.

This mechanism is particularly important for eco-innovation, which requires extensive environmental information processing, interdisciplinary collaboration, continuous technological learning, and long-term investment. Advanced digital ecosystems facilitate these processes by improving knowledge integration, supporting intelligent resource allocation, enhancing environmental monitoring, and enabling firms to optimize complex production and supply-chain systems [1,10].

Empirical evidence strongly supports these theoretical arguments. Studies consistently show that digital economy development promotes green innovation through improved information availability, technology diffusion, industrial upgrading, digital connectivity, and knowledge spillovers [11,28,47]. Regional evidence further indicates that digital economy development accelerates green innovation and sustainable development in emerging economies [20,29,30,38], while firm-level studies demonstrate that digital technologies, particularly when combined with absorptive capacity, significantly enhance green innovation performance [43,48]. Recent studies further show that the positive impact of AI capabil-

ity on innovation performance is substantially stronger in digitally advanced economies because superior digital infrastructure, innovation networks, and institutional support enhance firms' ability to convert AI investments into sustainable innovation [18,20,41,43,48].

Nevertheless, the benefits of digital economy development are not uniform across countries. Firms operating in less digitally developed economies often face constraints related to inadequate digital infrastructure, limited data availability, weaker technological capabilities, and shortages of digital skills, reducing the effectiveness of AI implementation. Accordingly, digital economy development does not independently generate eco-innovation; rather, it functions as a critical boundary condition that strengthens firms' ability to transform AI capability into environmentally sustainable innovation by providing the institutional, technological, and knowledge resources necessary for successful AI deployment.

Taken together, the theoretical arguments and empirical evidence indicate that digital economy development serves as a critical institutional and technological boundary condition influencing the effectiveness of AI capability. As digital infrastructure, connectivity, institutional support, and innovation ecosystems improve, firms become better positioned to integrate AI into innovation processes and convert technological investments into eco-innovation. Therefore, the positive relationship between AI capability and eco-innovation is expected to be stronger in countries with more developed digital economies.

H2. *Digital economy development positively moderates the relationship between AI capability and firms' eco-innovation.*

2.3. Conceptual Framework

Building upon the theoretical arguments and empirical evidence presented in the preceding sections, this study develops the conceptual framework illustrated in Figure 1. The framework integrates the NRBV, DCT, Institutional Theory, and the National Innovation Systems perspective to explain how firm-level AI capability and country-level digital economy development jointly influence eco-innovation. Specifically, AI capability is expected to enhance firms' environmental information processing, resource optimization, knowledge integration, and the development of environmentally sustainable products and processes. However, the effectiveness of AI capability depends on the external digital environment in which firms operate.

Digital economy development provides firms with advanced digital infrastructure, high-quality data resources, interconnected innovation networks, and supportive institutional environments that facilitate the effective deployment of AI technologies. Consequently, firms operating in digitally advanced economies are expected to exploit AI capability more effectively, enabling them to convert technological resources into superior eco-innovation outcomes than firms operating in less developed digital environments.

Accordingly, the proposed conceptual framework assumes that AI capability exerts a direct positive effect on firms' eco-innovation (H1), while digital economy development functions as a country-level boundary condition that strengthens this relationship (H2). Importantly, the framework adopts a multilevel perspective by linking firm-level AI capability with country-level digital economy development, thereby explaining how interactions between organizational capabilities and national digital environments shape firms' eco-innovation outcomes. Figure 1 summarizes the proposed relationships among the study variables and provides the theoretical foundation for the subsequent empirical analysis.

AI capability is hypothesized to positively influence firms' eco-innovation (H1). Digital economy development moderates this relationship (H2) by providing the institutional, technological, and digital infrastructure that enhances firms' ability to translate AI capability into environmentally sustainable innovation.

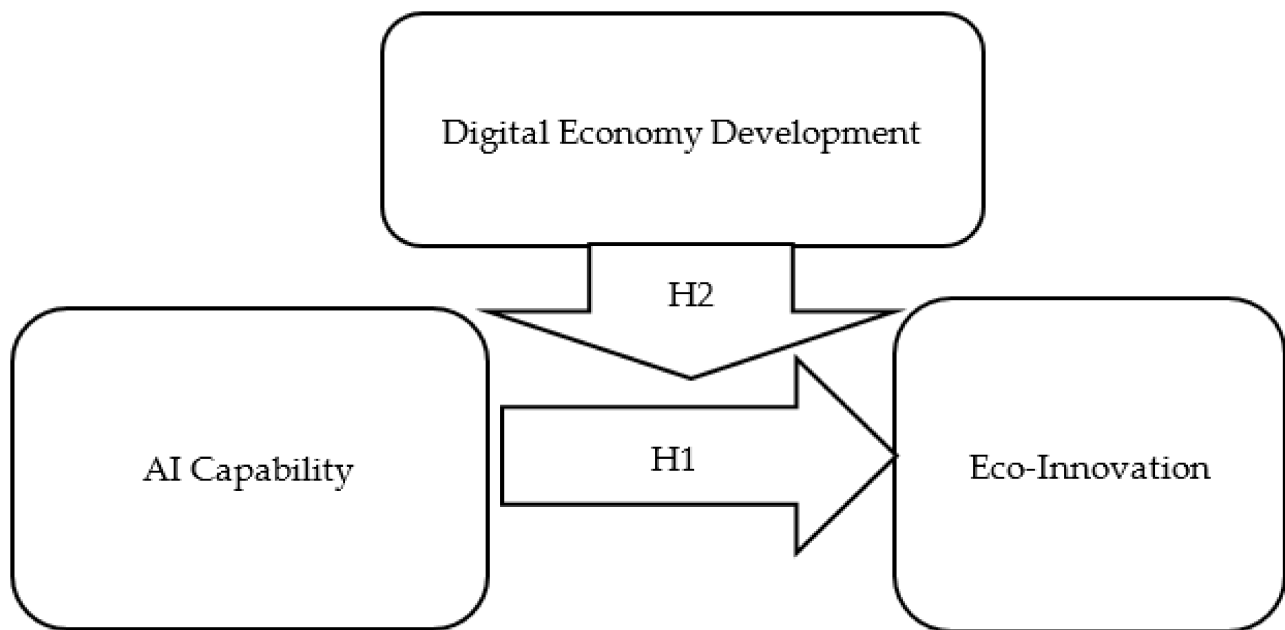


Figure 1. Conceptual Framework of the Study.

3. Methodology and Data

This study adopts a quantitative panel-data research design to investigate the relationship between AI capability and corporate eco-innovation (ECOINN), while examining the moderating role of digital economy development. A panel-data approach is appropriate because it enables the analysis of both cross-sectional differences among firms and temporal changes over time, while controlling for unobserved firm-specific heterogeneity and improving the reliability of causal inference. The empirical framework is grounded in the NRBV and DCT, which jointly explain how firms' technological capabilities and external digital environments influence their ability to generate sustainable innovation outcomes [14,35]. Within this perspective, AI represents a strategic technological resource that enhances firms' capacity to process complex data, optimize operations, and support environmentally efficient innovation activities. Consistent with the study's multilevel framework, the empirical design integrates firm-level AI capability with country-level digital economy development to examine how national digital environments shape firms' eco-innovation performance.

3.1. Sample and Data Sources

The analysis is based on a balanced panel dataset of 44,512 firm-year observations from 5564 publicly listed firms across Asian economies over the period 2017–2024. The final sample includes firms with complete information on the study variables. This multi-country design captures substantial variation in digital development and innovation capacity across the region. Asian economies provide a particularly suitable context for this study because they combine rapid digital transformation with increasing environmental pressures while exhibiting considerable heterogeneity in digital infrastructure, technological readiness, and institutional quality. Such differences create an appropriate empirical setting for examining how variations in national digital ecosystems influence firms' ability to convert AI capabilities into eco-innovation outcomes.

Firm-level data on eco-innovation, technological capability, and financial characteristics were obtained from the Refinitiv Eikon ESG and Company Fundamentals databases (Refinitiv, London, United Kingdom), which provide standardized and internationally comparable firm-level information widely used in sustainability, innovation, and corpo-

rate governance research [9,49]. Country-level indicators of digital economy development and institutional conditions were collected from multiple internationally recognized sources, including the World Bank's World Development Indicators (WDI), the International Telecommunication Union (ITU), the United Nations E-Government Development Index (UN EGDI), and the World Economic Forum's Network Readiness Index (NRI). These internationally recognized databases provide consistent cross-country measures of digital infrastructure, connectivity, digital governance, and technological readiness and have been widely adopted in recent digital economy research [34,50–53].

The key variables include AI capability, corporate eco-innovation, and digital economy development. Prior studies consistently show that firms with stronger AI and digital capabilities achieve higher levels of green innovation and environmental performance [11,12,36], while digital economy development enhances green technological innovation by improving digital infrastructure, data availability, knowledge spillovers, and technology diffusion [1,20,27,30,47]. The measurement and construction of all variables are presented in the following subsection.

Following established panel-data research practices, continuous variables were winsorized at the 1st and 99th percentiles, and logarithmic transformations were applied where appropriate to mitigate skewness and reduce the influence of extreme values.

3.2. Variable Construction

3.2.1. Dependent Variable: Eco-Innovation (ECOINN)

The dependent variable, eco-innovation (ECOINN), is measured using the Eco-Innovation Score (EIS) obtained from the Refinitiv Eikon ESG database. The EIS evaluates a firm's capacity to develop and implement environmentally sustainable technologies, products, and operational processes. The score is constructed from approximately twenty weighted indicators capturing eco-products, resource efficiency, emissions reduction, environmental innovation initiatives, and sustainable technology development. As a standardized ESG-based indicator, the EIS provides a comprehensive measure of firms' environmental innovation performance and has been widely employed in recent cross-country studies examining sustainability, green innovation, and digital transformation because of its consistency, international comparability, and broad firm coverage [11,49]. Recent evidence similarly adopts Refinitiv-based eco-innovation measures to evaluate firms' environmental innovation performance across different institutional settings.

The measurement framework aligns with the OECD Green Technology Classification and the European Union Environmental Goods and Services Sector (EGSS) methodology, ensuring that the indicator captures environmentally oriented innovation activities rather than conventional technological innovation [32,34,54].

To improve comparability and address potential skewness in the distribution, the raw score (0–100) is transformed as:

$$\text{ECOINN}_{i,t} = \ln(1 + \text{EIS}_{i,t}/100)$$

The logarithmic transformation reduces the influence of extreme observations, improves the normality of the distribution, and enhances comparability across firms, industries, and countries with different levels of eco-innovation performance. Similar transformations are commonly adopted in recent cross-country studies investigating AI, digital transformation, and sustainable innovation [55].

3.2.2. Independent Variable: AI Capability (AI_CAP)

AI_CAP is measured using a disclosure-based AI capability index derived from textual analysis of firms' annual reports and sustainability reports, following recent studies on

AI disclosure, digital transformation, and corporate AI adoption [12,19,56,57]. Disclosure-based AI measures have become increasingly adopted in recent research because they capture firms' strategic integration of AI technologies into business operations, innovation activities, and digital transformation through objective analysis of corporate disclosures, while providing scalable and internationally comparable measures of AI capability.

Specifically, AI-related content is identified using a predefined dictionary of AI-related keywords developed from prior AI disclosure studies, including artificial intelligence, machine learning, deep learning, automation, data analytics, intelligent systems, natural language processing, robotics, and predictive analytics. Consistent with prior textual-analysis studies, the frequency of these keywords is extracted from firms' annual and sustainability reports and normalized by the total number of words in each report to control for differences in disclosure length across firms and over time. This normalization enhances comparability across firm-year observations and mitigates reporting-size bias [15,19,34,43].

Formally, AI capability is calculated as follows:

$$AI_CAP_{i,t} = AI \text{ Keyword Frequency}_{i,t} / \text{Total Words}_{i,t}$$

The resulting ratio is subsequently standardized using z-score normalization to reduce scale heterogeneity and improve cross-sectional comparability across firms and countries. Similar disclosure-based and text-based AI measures have been widely employed in recent studies examining AI capability, corporate innovation, ESG performance, sustainability, and green transformation because they provide objective, transparent, and replicable proxies for firms' AI adoption and technological readiness [56,57].

Following [19], this textual-analysis approach provides an objective and data-driven proxy for AI capability by capturing firms' actual engagement with AI technologies as reflected in corporate narratives and strategic disclosures. Compared with survey-based or self-reported indicators, this approach reduces subjectivity, minimizes response bias, and enhances transparency and replicability. Recent studies further indicate that AI-related disclosures capture firms' technological readiness, digital transformation capability, information-processing capacity, and strategic commitment to AI implementation rather than merely symbolic reporting [48].

Overall, the AI_CAP measure is consistent with Dynamic Capability Theory (DCT), as it captures firms' ability to integrate, build, and continuously reconfigure digital resources and technological competencies to support eco-innovation, sustainability performance, and long-term competitive advantage. This conceptualization is consistent with recent evidence showing that AI capability strengthens organizational learning, information processing, innovation capability, and sustainable value creation [12,16,32,48].

3.2.3. Moderating Variable: Digital Economy Development (DIG_ECO)

Digital economy development (DIG_ECO) is included as a country-level moderating variable capturing the technological and institutional environment in which firms operate across Asian economies [26]. The variable reflects national digital advancement in terms of digital infrastructure, connectivity, digital skills, business digitalization, and digital public services. Recent studies emphasize that digital economy development represents a multidimensional ecosystem that facilitates firms' access to digital technologies, knowledge networks, data resources, and innovation infrastructure, thereby shaping firms' capacity to deploy AI and generate sustainable innovation [7,51,52]. Higher values therefore indicate more advanced digital ecosystems that facilitate the adoption, integration, and effective utilization of AI technologies.

DIG_ECO is proxied using a composite Digital Economy Index (DEI) constructed to ensure cross-country comparability. The index is based on four core dimensions relevant to

firm-level innovation outcomes: digital skills, digital infrastructure, business digitalization, and digital public systems, consistent with widely adopted digital economy frameworks and recent Digital Decade indicators [50,53]. These dimensions capture complementary aspects of national digital readiness that jointly determine firms' innovation opportunities rather than reflecting isolated technological characteristics [7,31].

The underlying indicators are collected from internationally recognized databases, including the World Bank (World Development Indicators), International Telecommunication Union (ITU), United Nations E-Government Development Index (UN EGDI), and the Network Readiness Index (NRI). These internationally recognized databases are widely employed in digital economy research because they provide standardized, reliable, and comparable cross-country indicators of digital infrastructure, connectivity, digital governance, and technological readiness [52,58].

All indicators are standardized, and Principal Component Analysis (PCA) is applied to extract the first principal component, which serves as the composite DIG_ECO score. PCA is a well-established technique for constructing composite indices because it objectively derives data-driven weights while efficiently summarizing the common variation among correlated indicators [7,53]. Recent studies similarly employ composite digital transformation indicators to capture the multidimensional nature of digital development and avoid measurement bias associated with relying on individual indicators [58].

The PCA results confirm the suitability of aggregating the selected indicators into a single composite index. All four dimensions loaded strongly and positively on the first principal component, with factor loadings ranging from 0.842 to 0.914. The first principal component had an eigenvalue of 3.18 and explained 79.46% of the total variance, indicating that the selected indicators capture a common underlying dimension of digital economy development. Accordingly, the first principal component was retained to construct the composite DIG_ECO. Detailed PCA results are reported in Appendix A Table A1.

As a contextual variable, DIG_ECO captures the macro-level digital environment that influences firms' ability to access digital infrastructure, exploit data resources, adopt advanced technologies, and translate AI investments into innovation outcomes. This country-level perspective is consistent with recent research showing that national digital ecosystems provide complementary resources that enhance firms' innovation capability beyond firm-specific technological investments [27,37]. Accordingly, DIG_ECO is introduced as a moderator to examine whether national digital conditions strengthen the relationship between AI capability and eco-innovation.

To test this moderating effect, an interaction term between AI_CAP and DIG_ECO is included in the regression model. All variables entering the interaction are mean-centered before estimation to reduce multicollinearity and facilitate interpretation of the interaction effects.

3.2.4. Control Variables

To mitigate omitted-variable bias, the analysis incorporates firm-level and country-level control variables that capture financial capacity, innovation investment, digital readiness, sustainability orientation, and macroeconomic conditions that may influence firms' eco-innovation activities. Specifically, profitability (ROA) is measured as net income divided by total assets and reflects firms' internal resources available for technological investment [11,36]. Firm size (SIZE), calculated as the natural logarithm of total assets, proxies organizational resources and absorptive capacity that facilitate innovation [49,59]. Research and development intensity (RDI), measured as research and development expenditure relative to total sales, captures firms' commitment to innovation activities [12].

In addition, ESG performance (ESG), obtained from the Refinitiv Eikon database and rescaled between 0 and 1, controls for firms' sustainability orientation and governance quality,

while digital capability (DIG_CAP) is included as a firm-level indicator of digital transformation and technological readiness [14,43]. Recent studies suggest that firms' digital readiness and sustainability orientation are important determinants of innovation performance [53].

At the country level, environmental regulation (ENV_REG) captures the stringency of environmental policies affecting corporate sustainability practices [25,48]. Inflation (INF) and economic growth (GDPG) are included to control for macroeconomic conditions that influence firms' investment behavior and innovation incentives. Finally, the models incorporate year, industry, and country fixed effects to control for time-specific shocks, sectoral characteristics, and cross-country institutional differences affecting eco-innovation outcomes.

3.3. Empirical Strategy

To examine the relationship between AI capability and corporate eco-innovation, this study employs firm fixed-effects panel estimations as the baseline specification. The fixed-effects model is appropriate because it controls for unobserved time-invariant firm characteristics that may jointly influence AI capability and eco-innovation, while year, industry, and country effects account for common shocks and institutional heterogeneity across firms and economies [60].

Although fixed effects substantially reduce omitted-variable bias, endogeneity may still arise from reverse causality, simultaneity, or omitted variables. Accordingly, several complementary robustness techniques are implemented to strengthen causal inference.

First, the two-step System GMM estimator is employed to address dynamic endogeneity, reverse causality, and simultaneity by using internal instruments based on lagged variables [61,62]. Second, the Heckman two-step model is applied to mitigate potential sample-selection bias arising from differences between firms with high and low levels of AI capability [63]. Third, PSM is conducted to improve comparability between treated and control firms based on observable characteristics, including firm size, profitability, and R&D intensity [64].

Model validity is assessed using standard diagnostic tests. The Hansen test evaluates instrument validity, while the Arellano–Bond AR(2) test examines second-order serial correlation. Robust standard errors clustered at the firm level are used in all estimations.

3.4. Variable Definitions

Table 1 summarizes the variables used in this study, including their definitions, measurement proxies, data sources, and supporting references. The measurement of AI capability, eco-innovation, and digital economy development follows established approaches in recent studies on AI adoption, digital transformation, and sustainable innovation [7,12,14] while the selection of control variables is consistent with prior cross-country panel studies on digital economy and environmental performance [11,26].

Table 1. Variable Definitions, Measurements, and References.

Variable	Variable	Proxy	Measurement/Description	References
Dependent Variable				
Eco-Innovation	ECOINN	EIS	Natural logarithm of (1 + Eco-Innovation Score/100) obtained from Refinitiv Eikon. The score aggregates approximately 20 indicators related to green products, resource efficiency, emission reduction, and sustainable technologies aligned with OECD and EGSS frameworks.	[11,59]
Independent Variable				
AI capability	AI_CAP	AI adoption index	Disclosure-based AI index measured as the ratio of AI-related keyword frequency to total word count in firms' reports.	[12,34]

Table 1. Cont.

Variable	Variable	Proxy	Measurement/Description	References
Digital economy development	DIG_ECO	Digital index	Moderator Country-level composite index capturing digital infrastructure, connectivity, digital skills, business digitalization, and digital public systems. Constructed using standardized indicators from the World Bank, ITU, UN, and WEF	[50,52,53]
			Control Variables	
Profitability	ROA	Return on assets	Net income divided by total assets, representing firms' operational efficiency and internal resources available for innovation investment.	[11]
Firm size	SIZE	ln_assets	Natural logarithm of total assets. Larger firms typically possess greater technological and financial capacity to invest in eco-innovation.	[18,50]
R&D intensity	RDI	R&D ratio	Research and development expenditure divided by total sales, capturing firms' innovation investment intensity.	[12]
ESG performance	ESG	ESG score	Environmental, social, and governance score from Refinitiv Eikon scaled between 0 and 1. Controls for sustainability orientation and governance quality.	Refinitiv
Digital capability	DIG_CAP	Digitalization	Firm-level digital technology adoption or digital transformation indicator.	[14,15]
Environmental regulation	ENV_REG	Policy index	Country-level environmental regulation or environmental policy indicator capturing regulatory pressure on firms.	[25,48]
Inflation	INF	CPI growth	Annual inflation rate based on consumer price index. Controls for macroeconomic stability and investment conditions.	World Bank
Economic growth	GDPG	GDP growth	Annual growth rate of GDP reflecting economic development and market demand conditions.	World Bank

Overall, this framework ensures conceptual clarity, measurement consistency, and comparability across firms, industries, and countries included in the sample.

3.5. Baseline Model

To test Hypothesis 1, this study estimates the relationship between AI capability and firms' eco-innovation using a firm fixed-effects panel regression model. The fixed-effects specification controls for unobserved time-invariant firm characteristics, such as managerial culture, organizational structure, and long-term technological orientation, which may jointly influence AI capability and eco-innovation [65]. Firm fixed effects reduce omitted-variable bias arising from unobservable heterogeneity, while year effects capture common macroeconomic shocks and technological changes affecting all firms over time. This specification provides a suitable baseline for identifying the within-firm effect of AI capability on eco-innovation across different industries and institutional environments [8].

The baseline model is specified as follows:

$$\text{ECOINN}_{i,t} = \alpha + \beta_1 \text{AI_CAP}_{i,t} + \beta_2 \text{Controls}_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (1)$$

where

- $\text{ECOINN}_{i,t}$ = Eco-innovation performance of firm i in year t , measured as the natural logarithm of one plus the Eco-Innovation Score.
- $\text{AI_CAP}_{i,t}$ = Disclosure-based AI capability index.
- $\text{Controls}_{i,t}$ = Vector of firm-level and country-level control variables.
- μ_i = Firm fixed effects.

- λ_t = Year fixed effects.
- $\varepsilon_{i,t}$ = Error term.

Standard errors are clustered at the firm level to correct for potential heteroskedasticity and serial correlation within firms over time [66].

3.6. Moderation Model

To test Hypothesis 2, the baseline model is extended by incorporating the moderating effect of DIG_ECO. Consistent with the theoretical framework, digital economy development represents a country-level contextual condition that influences firms' ability to leverage AI capability for sustainable innovation by providing digital infrastructure, connectivity, technological readiness, and knowledge resources. Recent studies similarly suggest that digitally advanced ecosystems strengthen firms' innovation capabilities by facilitating AI deployment and technology diffusion [7,31,51].

The moderation model is expressed as:

$$\text{ECOINN}_{i,t} = \alpha + \beta_1 \text{AI_CAP}_{i,t} + \beta_2 \text{DIG_ECO}_{c,t} + \beta_3 (\text{AI_CAP}_{i,t} \times \text{DIG_ECO}_{c,t}) + \beta_4 \text{Controls}_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (2)$$

where:

- $\text{DIG_ECO}_{c,t}$ = Digital economy development in country c at time t .
- $\text{AI_CAP}_{i,t} \times \text{DIG_ECO}_{c,t}$ = Interaction term capturing the conditional effect of digital development on the relationship between AI capability and eco-innovation.

Following standard practice in moderation analysis, AI_CAP and DIG_ECO are mean-centered before constructing the interaction term to reduce multicollinearity and facilitate coefficient interpretation [50]. A positive and statistically significant coefficient for β_3 indicates that the positive effect of AI capability on eco-innovation becomes stronger as the level of digital economy development increases, thereby supporting Hypothesis 2.

All control variables, fixed effects, and estimation procedures remain identical to those used in the baseline model to ensure consistency and comparability across specifications.

4. Results

4.1. Descriptive Statistics

Table 2 reports the descriptive statistics of the variables used in the analysis. The mean value of ECOINN is 0.462, indicating a moderate level of environmentally oriented innovation across the sampled firms. The AI_CAP has a mean close to zero (0.037), as expected following standardization, while its relatively large standard deviation (0.984) suggests substantial variation in firms' AI capability. The DIG_ECO averages 0.563, indicating noticeable differences in digital development across the sampled Asian economies.

Table 2. Summary Statistics.

Variable	Mean	SD	Min	Max	Skew.	Kurt.
ECOINN	0.462	0.311	0.000	1.832	0.89	3.12
AI_CAP	0.037	0.984	−2.614	3.428	0.41	2.57
DIG_ECO	0.563	0.147	0.221	0.892	−0.28	2.71
ROA	0.071	0.093	−0.214	0.384	−0.52	4.38
SIZE	15.842	1.721	11.203	20.764	0.36	2.94
RDI	0.043	0.058	0.000	0.321	1.92	6.44
ESG	0.548	0.203	0.081	0.912	−0.31	2.63
DIG_CAP	0.517	0.188	0.062	0.941	−0.22	2.74
ENV_REG	0.611	0.174	0.243	0.923	−0.47	2.81
INF	0.034	0.026	−0.012	0.118	0.88	3.76
GDPG	0.049	0.031	−0.041	0.102	−0.21	2.49

Among the control variables, firms exhibit moderate ESG performance (mean = 0.548) and digital capability (mean = 0.517), while R&D intensity shows considerable dispersion, reflecting heterogeneous innovation investment across firms. The observed variation across the main variables supports the use of panel estimation techniques to examine both within- and between-firm differences in eco-innovation performance. Furthermore, the skewness and kurtosis statistics indicate no serious departures from normality for most variables, suggesting that the data are suitable for the subsequent regression analyses.

4.2. Bivariate Correlations

Table 3 presents the Pearson correlation matrix and variance inflation factor (VIF) diagnostics. As expected, AI capability is positively and significantly associated with eco-innovation ($r = 0.421$, $p < 0.01$), providing preliminary support for Hypothesis 1. Similarly, the DEI is positively correlated with eco-innovation ($r = 0.356$, $p < 0.01$), suggesting that firms operating in more digitally developed environments tend to exhibit stronger eco-innovation performance.

Table 3. Correlation Matrix.

Variable	ECOINN	AI_CAP	DIG_ECO	ROA	SIZE	RDI	ESG	DIG_CAP	ENV_REG	INF	GDPG	VIF
ECOINN	1.000											—
AI_CAP	0.421 ***	1.000										1.83
DIG_ECO	0.356 ***	0.389 ***	1.000									1.67
ROA	0.214 ***	0.176 ***	0.102 ***	1.000								1.29
SIZE	0.287 ***	0.301 ***	0.198 ***	0.142 ***	1.000							1.54
RDI	0.338 ***	0.276 ***	0.121 ***	0.115 ***	0.204 ***	1.000						1.46
ESG	0.372 ***	0.318 ***	0.264 ***	0.192 ***	0.221 ***	0.238 ***	1.000					1.71
DIG_CAP	0.346 ***	0.407 ***	0.355 ***	0.129 ***	0.265 ***	0.244 ***	0.298 ***	1.000				1.79
ENV_REG	0.298 ***	0.252 ***	0.334 ***	0.081 **	0.117 ***	0.103 ***	0.269 ***	0.241 ***	1.000			1.44
INF	−0.063 **	−0.041 *	−0.072 **	−0.118 ***	−0.026	−0.034	−0.052 *	−0.038	−0.061 **	1.000		1.22
GDPG	0.095 ***	0.082 **	0.118 ***	0.144 ***	0.067 **	0.051 *	0.073 **	0.089 ***	0.062 **	−0.142 ***	1.000	1.31

*, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Among the control variables, ESG performance, firm size, R&D intensity, and digital capability also display positive and statistically significant associations with eco-innovation, consistent with prior research linking sustainability orientation, innovation investment, and digital readiness to environmental innovation. The remaining correlations are generally modest and follow the expected theoretical directions.

Importantly, none of the pairwise correlation coefficients exceed the commonly accepted threshold of 0.80, indicating that severe multicollinearity is unlikely. This conclusion is further supported by the VIF values, which range from 1.22 to 1.83, well below the conventional cut-off value of 5. Overall, these diagnostics suggest that multicollinearity is not a concern and that the variables are suitable for the subsequent regression analyses.

4.3. Baseline Regression Results

Table 4 reports the baseline fixed-effects regression results examining the relationship between AI capability and corporate eco-innovation. The diagnostic statistics support the suitability of the empirical specification. The F-test indicates that the models are jointly significant (Prob > F = 0.0000). The Breusch–Pagan test favors panel estimation over pooled OLS, while the Hausman test confirms the appropriateness of the fixed-effects estimator, indicating that unobserved firm-specific heterogeneity should be controlled for.

Model 1 includes only the control variables. Firm size, R&D intensity, ESG performance, and digital capability are positively associated with eco-innovation, suggesting that firms with stronger resources, innovation investments, and sustainability orientation achieve higher levels of environmentally oriented innovation. These findings are consistent

with the NRBV and DCT, which emphasize the strategic role of organizational resources and capabilities in driving sustainable innovation.

Table 4. Fixed-Effects Regression Results.

Variables	Model 1	ECOINN Model 2	Model 3
AI_CAP		0.128 *** (0.011)	0.121 *** (0.010)
ROA	0.064 *** (0.009)	0.052 *** (0.008)	0.047 *** (0.007)
SIZE	0.083 *** (0.006)	0.072 *** (0.006)	0.069 *** (0.005)
RDI	0.141 *** (0.018)	0.132 *** (0.017)	0.127 *** (0.016)
ESG	0.118 *** (0.014)	0.094 *** (0.013)	0.089 *** (0.012)
DIG_CAP	0.073 *** (0.012)	0.061 *** (0.011)	0.058 *** (0.010)
ENV_REG	0.049 ** (0.019)	0.041 ** (0.018)	0.039 ** (0.017)
INF	−0.021 (0.016)	−0.018 (0.015)	−0.017 (0.015)
GDPG	0.034 ** (0.014)	0.028 ** (0.013)	0.026 ** (0.012)
Constant	−0.842 *** (0.214)	−0.756 *** (0.198)	−0.691 *** (0.186)
Firm FE	No	Yes	Yes
Year FE	No	Yes	Yes
Country FE	No	No	Yes
Observations	44,512	44,512	44,512
No. of Groups	5564	5564	5,564
R ²	0.18	0.31	0.36
F-Test	142.37 ***	268.91 ***	301.44 ***
Prob > F	0.0000	0.0000	0.0000
Breusch–Pagan	5124.63 ***	5124.63 ***	5124.63 ***
Hausman		184.72 ***	184.72 ***

Notes: Robust standard errors are reported in parentheses. ** and *** indicate statistical significance at the 5% and 1% levels, respectively.

Model 2 introduces AI capability, which exhibits a positive and highly significant coefficient ($\beta = 0.128$, $p < 0.01$). This finding indicates that firms with stronger AI capability achieve higher levels of eco-innovation, supporting the argument that AI enhances firms' ability to develop environmentally sustainable products, processes, and technologies [12,15].

Model 3 presents the full specification with firm, year, and country fixed effects. The positive effect of AI capability remains statistically significant ($\beta = 0.121$, $p < 0.01$), confirming the robustness of the baseline results and providing strong support for Hypothesis 1. Furthermore, the model fit improves across specifications, with the R^2 increasing from 0.18 in Model 1 to 0.36 in Model 3, indicating that incorporating AI capability and fixed effects substantially enhances the explanatory power of the model. Overall, the findings suggest that AI capability is an important organizational capability that promotes eco-innovation by strengthening firms' capacity to generate sustainable technological innovations.

4.4. Moderation Analysis

Table 5 presents the moderation analysis. Model 1 reports the baseline specification, Model 2 introduces the interaction term between AI capability and digital economy development to test the proposed moderating effect, and Model 3 further incorporates country fixed effects to control for unobserved cross-country heterogeneity and provide a more stringent robustness check.

Across all three specifications, AI capability remains positively and statistically significantly associated with eco-innovation ($\beta = 0.097$ – 0.121 , $p < 0.01$). The interaction between AI capability and digital economy development is positive and statistically significant in Models 2 and 3 ($\beta = 0.047$ – 0.052 , $p < 0.01$), indicating that firms operating in more digitally developed economies are better able to translate AI capability into eco-innovation outcomes. The persistence of the interaction effect after introducing country fixed effects in Model 3 demonstrates that the findings are robust to unobserved cross-country heterogeneity.

Table 5. Regression Results of the Moderation Analysis.

Variables	Model 1	ECOINN Model 2	Model 3
AI_CAP	0.121 *** (0.010)	0.108 *** (0.011)	0.097 *** (0.012)
DIG_ECO	0.083 *** (0.017)	0.071 *** (0.016)	0.064 *** (0.015)
AI_CAP × DIG_ECO	—	0.052 *** (0.014)	0.047 *** (0.013)
ROA	0.046 *** (0.007)	0.044 *** (0.007)	0.042 *** (0.006)
SIZE	0.068 *** (0.005)	0.066 *** (0.005)	0.063 *** (0.005)
RDI	0.126 *** (0.016)	0.122 *** (0.016)	0.118 *** (0.015)
ESG	0.088 *** (0.012)	0.086 *** (0.011)	0.084 *** (0.011)
DIG_CAP	0.057 *** (0.010)	0.055 *** (0.010)	0.053 *** (0.009)
ENV_REG	0.038 ** (0.017)	0.037 ** (0.016)	0.035 ** (0.016)
INF	−0.017 (0.015)	−0.016 (0.015)	−0.015 (0.014)
GDPG	0.026 ** (0.012)	0.024 ** (0.011)	0.023 ** (0.011)
Constant	−0.684 *** (0.185)	−0.661 *** (0.179)	−0.632 *** (0.172)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Country FE	No	No	Yes
Observations	44,512	44,512	44,512
No. of Groups	5564	5564	5564
R ²	0.36	0.39	0.41
F-Test	301.44 ***	327.91 ***	344.18 ***
Prob > F	0.0000	0.0000	0.0000

Notes: Robust standard errors are reported in parentheses. ** and *** indicate statistical significance at the 5% and 1% levels, respectively.

This finding supports both the NRBV and DCT. From an NRBV perspective, the value of AI capability depends on complementary external resources provided by digitally advanced environments. From a DCT perspective, stronger digital infrastructure, connectivity, and knowledge networks enhance firms' ability to reconfigure AI-enabled resources into environmentally sustainable innovations.

The results are consistent with previous studies showing that digital transformation and technological ecosystems enhance green innovation and sustainability performance [16,36,67]. Unlike prior studies that primarily examine the direct effects of AI or digitalization, the present findings demonstrate that national digital economy development acts as an important contextual boundary condition that strengthens the positive effect of AI capability on eco-innovation.

From an econometric perspective, the models remain jointly significant (Prob > F = 0.0000), while the explanatory power improves from $R^2 = 0.36$ in the baseline model to $R^2 = 0.41$ after introducing the interaction term. These findings provide strong empirical support for Hypothesis 2.

4.5. Interaction Effects

To further examine the moderating role of DIG_ECO, a graphical analysis of the interaction effects was conducted. Following standard moderation procedures, conditional marginal effects were plotted to illustrate how the relationship between AI capability and eco-innovation varies across different levels of DIG_ECO [34,40]. The moderating variable was evaluated at low and high levels of digital economy development (± 1 standard deviation from the mean).

Figure 2 presents the interaction between AI capability and digital economy development on eco-innovation. The slopes are clearly non-parallel, indicating a moderating effect. Consistent with the regression results reported in Table 5, the positive relationship between AI capability and eco-innovation becomes stronger when digital economy development is higher. In contrast, when digital economy development is relatively low, the association between AI capability and eco-innovation remains positive but is noticeably weaker.

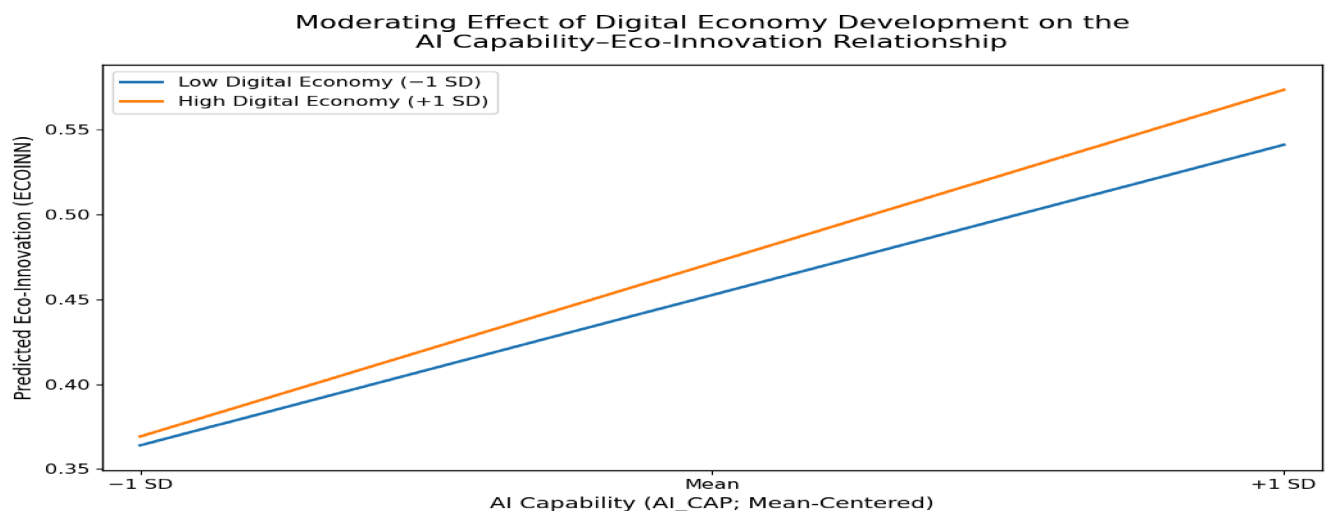


Figure 2. Interaction plot illustrating the moderating effect of digital economy development on the relationship between AI capability and eco-innovation.

These findings indicate that digital economy development enhances firms' ability to translate AI capability into environmentally sustainable innovation by strengthening digital infrastructure, improving data connectivity, facilitating knowledge diffusion, and accelerating technology adoption. Consequently, firms operating in digitally advanced environments are better positioned to leverage AI technologies to generate higher levels of eco-innovation. The interaction plot therefore complements the regression results by providing visual evidence of the moderating role of digital economy development. Overall, the graphical evidence provides additional support for Hypothesis 2, confirming that digital economy development strengthens the positive relationship between AI capability and eco-innovation.

5. Robustness Tests: Controlling for Endogeneity

The relationship between AI capability and corporate eco-innovation may be affected by endogeneity arising from non-random AI adoption, omitted variables, and reverse causality. Firms with stronger technological capabilities or sustainability orientation may be more likely to invest in AI while simultaneously exhibiting higher eco-innovation performance. Specifically, endogeneity may arise from self-selection, whereby technologically advanced firms are more likely to adopt AI; omitted firm-specific factors, such as managerial capability or innovation culture; and reverse causality, whereby firms with stronger eco-innovation subsequently increase AI investment [39,54,67].

Although the baseline fixed-effects models control for time-invariant firm heterogeneity, they may not fully eliminate these concerns. Therefore, additional robustness analyses are conducted using the two-step System GMM estimator, PSM, and the Heckman two-step selection model to verify that the main findings are not driven by endogeneity bias [12,14].

5.1. System GMM

To further address potential dynamic endogeneity, reverse causality, and simultaneity, the study employs the two-step System GMM estimator [62]. The dynamic specification includes the lagged dependent variable to capture persistence in firms' eco-innovation, while lagged internal instruments improve the consistency of the estimated coefficients. Model (1) reports the baseline dynamic specification, whereas Model (2) incorporates the interaction term between AI capability and digital economy development to examine the proposed moderating effect.

Table 6 reports the two-step System GMM results together with the diagnostic tests. The Hansen test is statistically insignificant ($p > 0.10$), confirming the validity of the instruments, while the Arellano–Bond tests indicate significant AR (1) but insignificant AR (2), suggesting the absence of second-order serial correlation. Moreover, the number of instruments remains substantially lower than the number of firms, reducing concerns regarding instrument proliferation [34,55].

Table 6. Endogeneity-Robust Analysis: Two-Step System GMM Estimates.

Variables	ECOINN	
	(1)	(2)
L.ECOINN ($t - 1$)	0.301 *** (0.038)	0.296 *** (0.037)
AI_CAP	0.028 ** (0.013)	0.019 * (0.010)
DIG_ECO	0.011 * (0.006)	0.010 * (0.006)
AI_CAP $\times$ DIG_ECO		0.015 ** (0.007)
ROA	0.007 *** (0.003)	0.008 *** (0.003)
SIZE	0.021 *** (0.006)	0.020 *** (0.006)
RDI	0.014 *** (0.004)	0.013 *** (0.004)
ESG	0.010 ** (0.005)	0.009 ** (0.005)
DIG_CAP	0.016 *** (0.005)	0.015 *** (0.005)
ENV_REG	0.012 ** (0.006)	0.011 ** (0.006)
GDPG	0.003 * (0.002)	0.003 * (0.002)
INF	−0.002 * (0.001)	−0.002 * (0.001)
AR (1) p -value	0.000	0.000
AR (2) p -value	0.291	0.314
Hansen J p -value	0.342	0.305
Year FE	Yes	Yes
Observations	44,512	44,512
Firms	5564	5564
Instruments	118	126

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

The lagged eco-innovation variable is positive and statistically significant ($\beta \approx 0.30$, $p < 0.01$), indicating persistence in firms' eco-innovation activities. In Model (1), AI capability remains positively and statistically significantly associated with eco-innovation ($\beta = 0.028$, $p < 0.05$), confirming that the baseline findings remain robust after controlling for dynamic endogeneity. In Model (2), the interaction between AI capability and digital economy development is positive and statistically significant ($\beta = 0.015$, $p < 0.05$), indicating that digitally advanced environments strengthen the positive effect of AI capability on eco-innovation. These findings provide additional support for Hypotheses 1 and 2 and demonstrate that the main results are robust to dynamic endogeneity.

5.2. PSM

Although the baseline fixed-effects models control for unobserved time-invariant heterogeneity, firms adopting advanced AI technologies may systematically differ from other firms in observable characteristics. AI-intensive firms are often larger, more profitable, and more digitally advanced, factors that may also influence eco-innovation outcomes. To mitigate potential selection bias arising from observable differences, the study employs PSM following prior research on digital innovation and sustainability [2,42,68].

Firms are classified as High-AI if their AI capability exceeds the sample median. A logit model is estimated to predict the probability of belonging to the treatment group using firm size, profitability, R&D intensity, ESG performance, digital capability, and macroeconomic variables. Treated firms are then matched with comparable control firms using nearest-neighbor matching with replacement.

Balance diagnostics indicate that the standardized differences across the matching covariates are substantially reduced after matching, confirming that the procedure successfully improves comparability between the treatment and control groups.

Table 7 shows that the matched-sample results remain consistent with the baseline estimations. AI capability continues to exert a positive and statistically significant effect on eco-innovation, while the interaction between AI capability and digital economy development also remains positive and significant. These findings indicate that the positive effects of AI capability and its interaction with the digital economy are not driven by observable differences between high-AI and low-AI firms.

Table 7. PSM Robustness Results.

Variables	Baseline FE	Matched Sample
AI_CAP	0.033 ** (0.015)	0.021 ** (0.010)
DIG_ECO	0.012 * (0.006)	0.010 * (0.006)
AI_CAP × DIG_ECO	0.008 *** (0.003)	0.007 *** (0.003)
SIZE	0.003 *** (0.001)	0.002 *** (0.001)
ROA	0.106 *** (0.020)	0.073 *** (0.017)
RDI	0.014 *** (0.004)	0.012 *** (0.004)
ESG	0.011 ** (0.005)	0.010 ** (0.005)
GDPG	0.002 ** (0.001)	0.001 ** (0.001)
INF	−0.002 ** (0.001)	−0.001 * (0.001)
Constant	0.148 *** (0.021)	0.152 *** (0.020)
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	44,512	44,512
Firms	5564	4812

Notes: Robust standard errors in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels. Propensity scores are estimated using firm characteristics, and matching is performed using nearest-neighbor matching with replacement. Firm and year fixed effects are included.

Overall, the PSM analysis provides additional evidence that the baseline findings are robust to selection bias based on observable firm characteristics, thereby reinforcing support for Hypotheses 1 and 2.

5.3. Heckman Two-Step Selection Model

Finally, the study applies the Heckman two-step selection model to further address potential sample-selection bias. Firms with higher AI capability may systematically differ from other firms in terms of technological readiness, managerial quality, innovation orientation, or access to digital infrastructure. If such characteristics simultaneously influence eco-innovation outcomes, the estimated relationships may be biased [63].

In the first stage, a probit model estimates the likelihood that a firm exhibits high AI capability based on observable firm characteristics, including firm size, profitability, R&D intensity, digital capability, and macroeconomic conditions. The estimated model is then used to compute the inverse Mills ratio (IMR), which captures potential sample-selection effects.

Table 8 reports the results of the Heckman two-step estimation. In the second stage, the IMR is incorporated into the eco-innovation regression model alongside AI capability, digital economy development, and their interaction term. The results indicate that AI capability remains positive and statistically significant, confirming the baseline finding that AI adoption enhances corporate eco-innovation. Likewise, the interaction between AI capability and digital economy development remains positive and statistically significant, indicating that firms operating in more digitally advanced environments are better able to translate AI investments into sustainable innovation outcomes [8,58,67].

Table 8. Heckman Two-Step Selection Model Results.

Variables	Selection Model (AI_CAP)	Outcome Model (ECOINN)
AI_CAP		0.020 * (0.011)
DIG_ECO		0.011 * (0.006)
AI_CAP $\times$ DIG_ECO		0.007 *** (0.003)
ROA	0.062 **	0.105 *** (0.020)
SIZE	0.214 ***	0.003 *** (0.001)
RDI	0.097 ***	0.013 *** (0.004)
ESG	0.081 **	0.010 ** (0.005)
DIG_CAP	0.135 ***	0.015 *** (0.005)
ENV_REG	0.044 *	0.011 ** (0.006)
GDPG	0.008 *	0.002 ** (0.001)
INF	−0.005	−0.002 * (0.001)
IMR (Lambda)		0.006
Constant		0.150 *** (0.021)
Year FE		Yes
Industry FE		Yes
Country FE		Yes
Observations	44,512	44,512
Firms	5564	5564

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Importantly, the coefficient of the IMR is statistically insignificant, suggesting that sample-selection bias is not a material concern in the estimated models. AI capability and the interaction between AI capability and digital economy development remain positive and statistically significant, indicating that the baseline findings are robust after accounting for potential selection effects. Overall, the Heckman results are consistent with the fixed-effects, System GMM, and PSM analyses, providing additional evidence that the main findings are robust and further supporting Hypotheses 1 and 2.

6. Heterogeneity Analysis

To further examine whether the impact of AI capability varies across different organizational and institutional contexts, additional heterogeneity analyses are conducted based on firm size and digital economy development. Prior research suggests that the effectiveness of AI depends not only on firm-level resources but also on the surrounding institutional and technological environment [3,59,60]. Accordingly, the sample is divided into subsamples to explore whether the relationship between AI capability and eco-innovation differs across firms with different resource endowments and countries with varying levels of digital development.

6.1. Heterogeneity by Firm Size

Table 9 reports the heterogeneity analysis based on firm size. The estimated coefficient of AI capability is larger for large firms ($\beta = 0.041$, $p < 0.01$) than for small firms ($\beta = 0.019$, $p < 0.05$), suggesting that organizational scale enhances firms' ability to translate AI capability into eco-innovation. Large firms generally possess greater financial resources, stronger absorptive capacity, more advanced technological infrastructure, and broader innovation networks, enabling them to deploy AI more effectively in support of sustainable innovation.

These findings are consistent with the NRBV, which emphasizes that firms with superior strategic resources and organizational capabilities are better positioned to generate sustainable competitive advantages. The results also align with previous studies showing that organizational resources and digital capabilities strengthen green innovation performance [4,12]. The regression models are jointly significant ($p < 0.001$), with higher explanatory power observed for the large-firm subsample (within $R^2 = 0.29$) than for the small-firm subsample (within $R^2 = 0.22$).

Table 9. Regression Results for Large and Small Firms.

Variables	Large Firms	Small Firms
AI_CAP	0.041 *** (0.009)	0.019 ** (0.008)
ROA	0.012 * (0.006)	0.008 (0.005)
SIZE	0.010 *** (0.003)	0.006 ** (0.003)
RDI	0.021 *** (0.006)	0.014 ** (0.005)
ESG	0.028 *** (0.007)	0.015 ** (0.006)
DIG_CAP	0.024 *** (0.006)	0.013 ** (0.006)
ENV_REG	0.017 ** (0.007)	0.009 * (0.005)
INF	−0.004 (0.003)	−0.006 * (0.003)
GDPG	0.009 ** (0.004)	0.006 * (0.003)
Constant	0.183 *** (0.041)	0.161 *** (0.039)
Observations	18,696	25,816
Firms	2337	3227
R ² (within)	0.29	0.22
F-test	48.37 ***	32.11 ***
Prob > F	0.0000	0.0000

Notes: The sample is divided based on the median value of firm size. All regressions include firm, industry, and year fixed effects with robust standard errors clustered at the firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

6.2. Heterogeneity by Digital Economy Development

Table 10 presents the heterogeneity analysis based on the level of digital economy development. The estimated coefficient of AI capability is larger in countries with high digital economy development ($\beta = 0.046$, $p < 0.10$) than in countries with lower digital economy development ($\beta = 0.018$, $p < 0.05$), suggesting that supportive digital environments enhance firms' ability to convert AI capability into eco-innovation.

Table 10. Regression Results for High- and Low-Digital Economy Countries.

Variables	High Digital Economy	Low Digital Economy
AI_CAP	0.046 * (0.010)	0.018 ** (0.009)
ROA	0.011 * (0.006)	0.007 (0.005)
SIZE	0.009 *** (0.003)	0.006 ** (0.003)
RDI	0.022 *** (0.006)	0.015 ** (0.005)
ESG	0.031 *** (0.007)	0.017 ** (0.006)
DIG_CAP	0.027 *** (0.007)	0.012 ** (0.006)
ENV_REG	0.019 ** (0.008)	0.010 * (0.006)
INF	−0.003 (0.003)	−0.005 * (0.003)
GDPG	0.010 ** (0.004)	0.006 * (0.003)
Constant	0.191 *** (0.042)	0.158 *** (0.038)
Observations	14,688	29,824
Firms	1836	3728
R ² (within)	0.31	0.23
F-test	51.42 ***	33.64 ***
Prob > F	0.0000	0.0000

Notes: Countries are classified into high and low digital economy groups based on the median value of the DEI. All regressions include firm, industry, and year fixed effects with robust standard errors clustered at the firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

These findings complement the moderation analysis by indicating that digital infrastructure, connectivity, technological readiness, and knowledge networks reinforce the effectiveness of AI capability. From the perspective of DCT, digitally advanced environments facilitate firms' ability to integrate, reconfigure, and leverage AI-enabled resources to generate environmentally sustainable innovations.

The results are consistent with previous evidence showing that digital transformation and technological ecosystems promote green innovation and sustainability performance [53,56]. The models remain jointly significant ($p < 0.001$), with higher explanatory power in digitally

advanced economies (within $R^2 = 0.31$) than in less digitally developed economies (within $R^2 = 0.23$).

7. Discussion

This study examined the effect of AI capability on firms' eco-innovation and the moderating role of digital economy development using a large panel of Asian firms. The findings provide strong support for Hypotheses 1 and 2, demonstrating that AI capability enhances firms' eco-innovation and that this relationship becomes stronger in countries with more advanced digital economies.

First, the results indicate that AI capability positively influences eco-innovation, supporting Hypothesis 1. This finding is consistent with previous studies showing that AI enhances environmental innovation by improving knowledge integration, resource optimization, operational efficiency, and organizational learning [4,5,39]. Our results also agree with recent evidence that AI functions as a general-purpose technology capable of transforming production systems and accelerating sustainable innovation when effectively integrated into organizational processes [18].

Furthermore, the findings support studies emphasizing that AI creates greater organizational value when combined with complementary organizational capabilities, implementation readiness, and digital resources [20,21]. From a theoretical perspective, these findings reinforce the NRBV by demonstrating that AI capability represents a strategic resource that enables firms to generate both environmental and competitive advantages through eco-innovation.

Second, the results show that digital economy development positively moderates the relationship between AI capability and eco-innovation, providing strong support for Hypothesis 2. As illustrated in Figure 2, the positive relationship between AI capability and eco-innovation becomes considerably stronger under higher levels of digital economy development, whereas the association remains positive but noticeably weaker in less digitally developed environments. The interaction plot provides clear graphical evidence that AI capability generates substantially greater eco-innovation gains when firms operate within digitally advanced environments, highlighting the complementary role of national digital ecosystems in enhancing the value of AI investments.

This finding is consistent with previous research reporting that advanced digital infrastructure, digital connectivity, knowledge spillovers, and supportive institutional environments enable firms to utilize AI more effectively for innovation and sustainability [20,30,41,48]. Our findings extend this literature by demonstrating that digital economy development not only promotes innovation directly but also strengthens the effectiveness of firm-level AI capability in generating eco-innovation. These results are consistent with DCT, Institutional Theory, and the National Innovation Systems (NIS) perspective, suggesting that firms are better able to transform AI-enabled resources into eco-innovation when operating within supportive digital ecosystems.

Third, the heterogeneity analyses indicate that the estimated effect of AI capability is larger among large firms and firms operating in digitally advanced economies. These findings are consistent with earlier studies showing that firms with greater absorptive capacity, stronger technological infrastructure, richer data resources, and broader innovation networks obtain greater innovation benefits from digital technologies [1,29,38,47]. Likewise, firms operating in countries with more developed digital ecosystems benefit from superior digital infrastructure, institutional support, and knowledge-sharing networks, allowing them to deploy AI technologies more effectively for environmentally sustainable innovation. Collectively, these findings suggest that AI capability alone is insufficient to maximize eco-

innovation; rather, its effectiveness depends on complementary organizational resources and supportive national digital environments.

This study makes several theoretical contributions. First, it extends the Natural Resource-Based View by conceptualizing AI capability as a strategic technological resource that strengthens firms' environmental innovation performance. Second, it advances Dynamic Capability Theory by demonstrating that national digital ecosystems constitute an important contextual condition influencing firms' ability to transform AI capability into sustainable innovation outcomes. Third, by integrating firm-level AI capability with country-level digital economy development, the study contributes to the growing literature on digital transformation and sustainability through a multilevel perspective that links organizational capabilities with institutional environments.

The findings also have important practical implications. For managers, the results suggest that investments in AI should be accompanied by complementary investments in digital skills, organizational capabilities, data management, and innovation processes to maximize eco-innovation outcomes. Firms operating in less digitally developed environments should strengthen internal technological capabilities and strategic collaborations to overcome institutional constraints. For policymakers, the findings highlight the importance of investing in digital infrastructure, innovation ecosystems, digital skills, and supportive regulatory frameworks that facilitate AI adoption and sustainable innovation. Strengthening national digital ecosystems can accelerate digital transformation while simultaneously supporting environmentally sustainable economic growth.

Finally, this study offers several directions for future research. Future studies could examine whether different AI technologies, such as machine learning, generative AI, computer vision, or predictive analytics, have heterogeneous effects on eco-innovation. Researchers may also investigate additional contextual moderators, including environmental regulation, corporate governance, institutional quality, or ESG performance, and extend the analysis to other regions to evaluate the generalizability of the findings. Longitudinal and mixed-method studies could further improve understanding of how firms develop AI capabilities and integrate them into long-term sustainability strategies.

8. Conclusions

This study examined the impact of AI capability on firms' eco-innovation and the moderating role of digital economy development using a balanced panel of listed Asian firms from 2017 to 2024. The findings provide robust evidence that AI capability positively influences eco-innovation and that this relationship remains consistent across alternative model specifications, moderation analyses, heterogeneity analyses, and multiple robustness tests.

The study offers several important insights. First, firms with stronger AI capability achieve higher levels of eco-innovation, suggesting that AI enhances firms' ability to improve resource efficiency, optimize environmental decision-making, and develop sustainable products and processes. Second, the positive impact of AI capability is stronger in countries with more advanced digital economies, indicating that digital infrastructure, connectivity, and innovation ecosystems reinforce firms' ability to translate AI investments into environmentally sustainable innovation. Third, the heterogeneity analyses show that the estimated effect of AI capability is larger among large firms, highlighting the importance of organizational resources, technological readiness, and absorptive capacity in maximizing the environmental benefits of AI.

Overall, the findings demonstrate that the sustainability value of AI depends not only on firms' technological capabilities but also on the quality of the surrounding digital ecosystem. Beyond confirming the positive role of AI capability, this study contributes to the literature on digital transformation, sustainability, and innovation by providing a

multilevel perspective that integrates firm-level AI capability with country-level digital economy development. The findings further extend the NRBV and DCT by demonstrating that supportive digital environments strengthen firms' ability to transform technological resources into environmentally sustainable innovation.

Despite these contributions, several limitations should be acknowledged. First, although this study employs a large cross-country sample, the analysis is limited to publicly listed firms in Asia, which may restrict the generalizability of the findings to private firms or other institutional and geographical contexts. Second, although the AI capability measure is derived from objective textual analysis of corporate disclosures, it may not fully capture firms' actual AI adoption, technological sophistication, or the operational integration of AI systems. Consequently, the measure may partly reflect firms' disclosure practices rather than their underlying AI capabilities. Third, although the empirical analysis employs firm fixed-effects models, System GMM, PSM, and the Heckman two-step approach to mitigate endogeneity and sample-selection concerns, unobserved firm- or country-level factors may still influence the relationship between AI capability and eco-innovation. Future research could extend this work by examining other institutional settings, incorporating alternative measures of AI capability based on patents, investments, or operational AI deployment, and exploring additional contextual factors that may shape AI-enabled eco-innovation.

Future research could extend this study by examining firms from other regions, such as Europe, North America, and emerging economies, to assess the generalizability of the findings across different institutional environments. Researchers may also employ alternative measures of AI capability, digital transformation, and technological maturity to capture different dimensions of organizational digitalization. In addition, future studies could investigate the effects of specific AI technologies, such as generative AI, machine learning, and predictive analytics, on different dimensions of eco-innovation and sustainability performance. Finally, further research may explore how AI capability interacts with other governance and sustainability mechanisms, including ESG practices, environmental regulation, green finance, and corporate governance, to advance environmentally sustainable innovation.

Author Contributions: Conceptualization, M.M. and A.A.; methodology, M.M. and I.Y.Y.; software, I.Y.Y.; validation, M.M., A.A. and M.A.; formal analysis, M.M. and I.Y.Y.; investigation, M.M. and A.A.; resources, A.A. and M.A.; data curation, I.Y.Y. and M.A.; writing—original draft preparation, M.M.; writing—review and editing, I.Y.Y., A.A. and M.A.; visualization, I.Y.Y.; supervision, M.M.; project administration, M.M.; funding acquisition, A.A. and M.A. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the Deanship of Scientific Research, Vice Presidency for Graduate Studies and Scientific Research, King Faisal University, Saudi Arabia (No. KFU264063).

Data Availability Statement: The firm-level data supporting the findings of this study were obtained from Refinitiv Eikon under a commercial license and are therefore not publicly available. These data are available from Refinitiv Eikon with the appropriate license or from the corresponding author upon reasonable request, subject to Refinitiv's licensing restrictions. Country-level data were obtained from publicly available sources, including the World Bank, the International Telecommunication Union (ITU), the United Nations E-Government Development Index (UN EGDI), and the World Economic Forum's Network Readiness Index (NRI).

Acknowledgments: The authors gratefully acknowledge the academic and institutional support provided by Amman Arab University, Jordan, and King Faisal University, Saudi Arabia, which facilitated the completion of this research. The authors also appreciate the access to institutional research resources and databases that supported this study.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
AI_CAP	Artificial Intelligence Capability
ECOINN	Eco-Innovation
EIS	Eco-Innovation Score
DIG_ECO	Digital Economy Development
DIG_CAP	Digital Capability
NRBV	Natural Resource-Based View
DCT	Dynamic Capability Theory
PSM	Propensity Score Matching
GMM	Generalized Method of Moments
ESG	Environmental, Social, and Governance
RDI	Research and Development Intensity
ROA	Return on Assets
SIZE	Firm Size
ENV_REG	Environmental Regulation
INF	Inflation
GDPG	Gross Domestic Product Growth
PCA	Principal Component Analysis
DEI	Digital Economy Index

Appendix A

Table A1. Principal Component Analysis (PCA) of the DEI.

Digital Economy Dimension	PC1 Loading
Digital Skills	0.842
Digital Infrastructure	0.914
Business Digitalization	0.901
Digital Public Services	0.881
Eigenvalue (PC1): 3.18	
Explained Variance: 79.46%	
Cumulative Variance: 79.46%	

Note: All indicators exhibit strong positive loadings on the first principal component, confirming that they capture a common underlying dimension of digital economy development. The first principal component explains 79.46% of the total variance and was therefore retained to construct the composite DEI.

References

1. He, W.-W.; He, S.-L.; Hou, H.-L. Digital economy, technological innovation, and sustainable development. *PLoS ONE* **2024**, *19*, e0305520. [[CrossRef](#)] [[PubMed](#)]
2. An, Q.; Wang, R.; Wang, Y.; Pavel, K. The impact of the digital economy on sustainable development: Evidence from China. *Front. Environ. Sci.* **2024**, *12*, 1341471. [[CrossRef](#)]
3. Xu, C.; Lin, B. The AI-sustainability Nexus: How does intelligent transformation affect corporate green innovation? *Int. Rev. Financ. Anal.* **2025**, *102*, 104107. [[CrossRef](#)]
4. Liu, Y.; Shen, F.; Guo, J.; Hu, G.; Song, Y. Can artificial intelligence technology improve companies' capacity for green innovation? Evidence from listed companies in China. *Energy Econ.* **2025**, *143*, 108280. [[CrossRef](#)]
5. Mijit, R.; Hu, Q.; Xu, J.; Ma, G. Greening through AI? The impact of artificial intelligence innovation and development pilot zones on green innovation in China. *Energy Econ.* **2025**, *146*, 108507. [[CrossRef](#)]
6. United Nations Conference on Trade and Development (UNCTAD). *United Nations Conference on Trade and Development (UNCTAD), Digital Economy Report 2024: Shaping an Environmentally Sustainable and Inclusive Digital Future*; Stylus Publishing, LLC: Sterling, VA, USA, 2024.
7. Laitso, E.; Katsianis, D.; Xenakis, A.; Gerogiannis, V.C. Pacing the digital decade: Digital evolution and its impact on human well-being. *Telecommun. Policy* **2025**, *49*, 102868. [[CrossRef](#)]

8. Arfanuzzaman, M. Harnessing artificial intelligence and big data for SDGs and prosperous urban future in South Asia. *Environ. Sustain. Indic.* **2021**, *11*, 100127. [\[CrossRef\]](#)
9. Farmanesh, P.; Solati Dehkordi, N.; Vehbi, A.; Chavali, K. Artificial intelligence and green innovation in small and medium-sized enterprises and competitive-advantage drive toward achieving sustainable development goals. *Sustainability* **2025**, *17*, 2162. [\[CrossRef\]](#)
10. Hong, Z.; Xiao, K. Digital economy structuring for sustainable development: The role of blockchain and artificial intelligence in improving supply chain and reducing negative environmental impacts. *Sci. Rep.* **2024**, *14*, 3912. [\[CrossRef\]](#) [\[PubMed\]](#)
11. Dong, X.; Zhou, N.; Zhao, X.; Yang, S. The impact of artificial intelligence on corporate green innovation: Can “increasing quantity” and “improving quality” go hand in hand? *J. Environ. Manag.* **2025**, *376*, 124439. [\[CrossRef\]](#)
12. Feng, F.; Li, J.; Zhang, F.; Sun, J. The impact of artificial intelligence on green innovation efficiency: Moderating role of dynamic capability. *Int. Rev. Econ. Financ.* **2024**, *96*, 103649. [\[CrossRef\]](#)
13. Suárez Giri, F.; Sánchez Chaparro, T. Unveiling the blackbox within ESG ratings’ blackbox: Toward a framework for analyzing AI adoption and its impacts. *Bus. Strategy Dev.* **2024**, *7*, e70038. [\[CrossRef\]](#)
14. Lin, J.; Zeng, Y.; Wu, S.; Luo, X.R. How does artificial intelligence affect the environmental performance of organizations? The role of green innovation and green culture. *Inf. Manag.* **2024**, *61*, 103924. [\[CrossRef\]](#)
15. Wang, Z.; Zhang, T.; Ren, X.; Shi, Y. AI adoption rate and corporate green innovation efficiency: Evidence from Chinese energy companies. *Energy Econ.* **2024**, *132*, 107499. [\[CrossRef\]](#)
16. Xi, K.; Shao, X. Impact of AI applications on corporate green innovation. *Int. Rev. Econ. Financ.* **2025**, *99*, 104007. [\[CrossRef\]](#)
17. Matamoros-Echeverria, K.L.; Sanchez-Leon, E.R.; Aristega-Zuñiga, A.A.; Cárdenas-Rodríguez, M.M.; Peralta-Gamboa, D.A. The Impact of Artificial Intelligence on the Digital Economy: Advances and Challenges-A Systematic Literature Review. *J. Posthumanism* **2025**, *5*, 219–235. [\[CrossRef\]](#)
18. Ma, Y.; Zhang, W.; Ma, C.; Ai, Y.; Hu, J. Artificial intelligence, data elements, digital economy, and corporate innovation performance. *Int. Rev. Econ. Financ.* **2025**, *103*, 104560. [\[CrossRef\]](#)
19. Zhong, K.; Song, L. Artificial intelligence adoption and corporate green innovation capability. *Financ. Res. Lett.* **2025**, *72*, 106480. [\[CrossRef\]](#)
20. Chen, Z.; Xing, R. Digital economy, green innovation and high-quality economic development. *Int. Rev. Econ. Financ.* **2025**, *99*, 104029. [\[CrossRef\]](#)
21. Ozay, D.; Jahanbakht, M.; Wang, S. What resources are needed for effective AI implementation in CRM, and does it actually enhance performance? *Electron. Commer. Res. Appl.* **2025**, *74*, 101552. [\[CrossRef\]](#)
22. Huang, Y.; Liu, S.; Gan, J.; Liu, B.; Wu, Y. How does the construction of new generation of national AI innovative development pilot zones drive enterprise ESG development? Empirical evidence from China. *Energy Econ.* **2024**, *140*, 108011. [\[CrossRef\]](#)
23. Song, Y.; Zhang, Y.; Zhang, Z.; Sahut, J.M. Artificial intelligence, digital finance, and green innovation. *Glob. Financ. J.* **2025**, *64*, 101072. [\[CrossRef\]](#)
24. Tan, Y.; Huang, X.; Shu, R.; Ren, X.; Huang, X.; Chen, Q. The Impact of the Digital Economy on the Forest Food Industry: Mechanisms and Evidence from China. *J. Agric. Food Res.* **2026**, *27*, 102745. [\[CrossRef\]](#)
25. Yin, K.; Cai, F.; Huang, C. How does artificial intelligence development affect green technology innovation in China? Evidence from dynamic panel data analysis. *Environ. Sci. Pollut. Res.* **2023**, *30*, 28066–28090.
26. Xu, J.; Lee, T.; Goggin, G. AI governance in Asia: Policies, praxis and approaches. *Commun. Res. Pract.* **2024**, *10*, 275–287. [\[CrossRef\]](#)
27. Bu, W.; Yan, Z.; Yang, S. Digital economy and corporate sustainability: Mediating roles of green innovation and risk-taking. *Financ. Res. Lett.* **2025**, *78*, 107200. [\[CrossRef\]](#)
28. Qiao, P.; Liu, S.; Fung, H.G.; Wang, C. Corporate green innovation in a digital economy. *Int. Rev. Econ. Financ.* **2024**, *92*, 870–883. [\[CrossRef\]](#)
29. Chen, K.; Zhao, S.; Jiang, G.; He, Y.; Li, H. The green innovation effect of the digital economy. *Int. Rev. Econ. Financ.* **2025**, *99*, 103970. [\[CrossRef\]](#)
30. Chen, Z.; Xu, W. The role of the digital economy in enhancing green innovation: Evidence from Chinese A-share listed enterprises. *Financ. Res. Lett.* **2025**, *71*, 106381. [\[CrossRef\]](#)
31. Privara, A.; Caplanova, A. Institutions, digital investment potential and productivity growth in EU and Southeast Asia. *J. Risk Financ.* **2025**, *26*, 722–744. [\[CrossRef\]](#)
32. Saleh, M.W.; Mansour, M.; Jaradat, Z.; Al-Hawamleh, A.M. Innovative sustainability: How artificial intelligence disclosure enhances the risk-reducing effect of ESG performance. *Int. J. Product. Perform. Manag.* **2026**, 1–18. [\[CrossRef\]](#)
33. Chun, Y.; Hwang, J. The nexus of artificial intelligence and green innovation: A cross-density analysis at the country level. *J. Knowl. Econ.* **2025**, *16*, 1688–1716.
34. Mansour, M.; Zobi, M.T.A.; Marei, A.; Daoud, L.; Kurdi, N.I. AI-Enabled Governance: Board Gender Diversity and Corporate Tax Avoidance. *Computation* **2026**, *14*, 97. [\[CrossRef\]](#)

35. Barney, J.B.; Arikan, A.M. The resource-based view: Origins and implications. In *The Blackwell Handbook of Strategic Management*; Blackwell Publishers Ltd: Hoboken, NJ, USA, 2005; pp. 123–182.
36. Hussain, M.; Yang, S.; Maqsood, U.S.; Zahid, R.A. Tapping into the green potential: The power of artificial intelligence adoption in corporate green innovation drive. *Bus. Strategy Environ.* **2024**, *33*, 4375–4396. [\[CrossRef\]](#)
37. Song, S.; Wen, J.; Li, Y.; Li, L. How does digital economy affect green technological innovation in China? New evidence from the “Broadband China” policy. *Econ. Anal. Policy* **2024**, *81*, 1093–1112. [\[CrossRef\]](#)
38. Chen, Y.; Jin, S. Artificial intelligence and carbon emissions in manufacturing firms: The moderating role of green innovation. *Processes* **2023**, *11*, 2705. [\[CrossRef\]](#)
39. Liang, P.; Sun, X.; Qi, L. Does artificial intelligence technology enhance green transformation of enterprises: Based on green innovation perspective. *Environ. Dev. Sustain.* **2024**, *26*, 21651–21687. [\[CrossRef\]](#)
40. Chong, Y.W.; Villanueva-Libunao, K.; Chee, S.Y.; Alvarez, M.J.; Yau, K.L.A.; Keoh, S.L. Artificial intelligence policies to enhance urban mobility in Southeast Asia. *Front. Sustain. Cities* **2022**, *4*, 824391. [\[CrossRef\]](#)
41. Ma, D.; Zhu, Q. Innovation in emerging economies: Research on the digital economy driving high-quality green development. *J. Bus. Res.* **2022**, *145*, 801–813. [\[CrossRef\]](#)
42. Umair, M.; Gulzar, F.; Ur Rahman, S. Digital green governance and ESG outcomes: How executive digital orientation drives sustainable transformation in China’s mining enterprises. *Miner. Econ.* **2025**, 1–15.
43. Huang, Y.; Liu, S.; Gan, J.; Liu, B.; Wu, Y. How Does the Construction of New Generation of National AI Innovative Development Pilot Zones Affect Carbon Emissions Intensity? Empirical Evidence from China. *Sustainability* **2025**, *17*, 6858. [\[CrossRef\]](#)
44. Powell, W.W.; DiMaggio, P.J. *The New Institutionalism in Organizational Analysis*; University of Chicago Press: Chicago, IL, USA, 2012.
45. Diodato, D.; Huergo, E.; Moncada-Paternò-Castello, P.; Rentocchini, F.; Timmermans, B. Introduction to the special issue on “the twin (digital and green) transition: Handling the economic and social challenges”. *Ind. Innov.* **2023**, *30*, 755–765. [\[CrossRef\]](#)
46. Hao, X.; Li, Y.; Wang, K.; Sun, Q.; Wu, H. Eco-intelligent production: Intelligent manufacturing and industrial green transition. *Environ. Dev. Sustain.* **2025**, 1–31. [\[CrossRef\]](#)
47. Ge, Y.; Xia, Y.; Wang, T. Digital economy, data resources and enterprise green technology innovation: Evidence from A-listed Chinese Firms. *Resour. Policy* **2024**, *92*, 105035. [\[CrossRef\]](#)
48. Zhou, Z.; Yuan, Z.; He, C. Can digital transformation promote firms’ sustainable development? Evidence based on ESG performance. *Int. Rev. Financ. Anal.* **2025**, *105*, 104434. [\[CrossRef\]](#)
49. Li, X.; Zhang, Y.; Zhou, S.; Zhao, Z.; Zhao, Y. Exploration and future trends on spatial correlation of green innovation efficiency in strategic emerging industries under the digital economy: A social network analysis. *J. Environ. Manag.* **2024**, *359*, 121005. [\[CrossRef\]](#)
50. Mansour, M.; Saleh, M.W.; Jaradat, Z.; Al-Hawamleh, A.; Al Zobi, M.T.; Marei, A. Digital economy development and firm level sustainability performance in Europe. *Discov. Sustain.* **2026**, *7*, 322. [\[CrossRef\]](#)
51. Imran, M.; Liu, X.; Wang, R.; Saud, S.; Zhao, Y.; Khan, M.J. The influence of digital economy and society index on sustainable development indicators: The case of European Union. *Sustainability* **2022**, *14*, 11130. [\[CrossRef\]](#)
52. Lafuente, E.; Ács, Z.J.; Szerb, L. Analysis of the digital platform economy around the world: A network DEA model for identifying policy priorities. *J. Small Bus. Manag.* **2024**, *62*, 847–891.
53. Várzaru, A.A. Unveiling digital transformation: A catalyst for enhancing food security and achieving sustainable development goals at the European union level. *Foods* **2024**, *13*, 1226. [\[CrossRef\]](#) [\[PubMed\]](#)
54. Fu, H.; Li, M.; Guo, W.; Huang, J. Digital transformation and carbon reduction: Evidence from Chinese listed companies. *Financ. Res. Lett.* **2025**, *83*, 107652. [\[CrossRef\]](#)
55. Mansour, M.; Zobi, M.T.A.; Alomair, M. Artificial Intelligence, ESG Governance, and Green Innovation Efficiency in Emerging Economies. *Economies* **2025**, *14*, 11. [\[CrossRef\]](#)
56. Xie, H.; Wu, F. Artificial intelligence technology and corporate ESG performance: Empirical evidence from Chinese-listed firms. *Sustainability* **2025**, *17*, 420. [\[CrossRef\]](#)
57. Zhang, C.; Yang, J. Artificial intelligence and corporate ESG performance. *Int. Rev. Econ. Financ.* **2024**, *96*, 103713. [\[CrossRef\]](#)
58. Vasconcelos-Garcia, M.; Carrilho-Nunes, I. Internationalisation and digitalisation as drivers for eco-innovation in the European Union. *Struct. Change Econ. Dyn.* **2024**, *70*, 245–256. [\[CrossRef\]](#)
59. Qamhan, M.A.; Mansour, M.; Zobi, M.T.A.; Saleh, M.W.; Alomair, A.; Alshdaifat, S.M. Does Size Matter for Green Growth? Endogenous Size Thresholds in the Eco-Innovation–Performance Nexus. *Risks* **2026**, *14*, 139. [\[CrossRef\]](#)
60. Mansour, M.; Al Zobi, M.T.K.; Al-Naimi, A.; Daoud, L. The connection between Capital structure and performance: Does firm size matter? *Invest. Manag. Financ. Innov.* **2023**, *20*, 195–206. [\[CrossRef\]](#)
61. Blundell, R.; Bond, S. Initial conditions and moment restrictions in dynamic panel data models. *J. Econom.* **1998**, *87*, 115–143. [\[CrossRef\]](#)
62. Arellano, M.; Bond, S. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Rev. Econ. Stud.* **1991**, *58*, 277–297. [\[CrossRef\]](#)

63. Heckman, J.J. Sample selection bias as a specification error. *Econom. J. Econom. Soc.* **1979**, *47*, 153–161. [[CrossRef](#)]
64. Rosenbaum, P.R.; Rubin, D.B. The central role of the propensity score in observational studies for causal effects. *Biometrika* **1983**, *70*, 41–55. [[CrossRef](#)]
65. Al-Tahat, S.; Bani-Khaled, S.; Jaradat, Z.; Mansour, M.; Al-Zoubi, A.M. State ownership as a moderator in the relationship between board characteristics and ESG performance: Evidence from Asia-Pacific markets. *J. Bus. Socio-Econ. Dev.* **2025**, 1–22. [[CrossRef](#)]
66. Saleh, M.W.; Mansour, M.; Shubita, M.F.; Lutfi, A.; Salah, W.; Rehman, S.U. Does ISO 14001 Boost Energy Firm's Financial Performance? The Moderating Role of Environmental, Social, and Governance. *Corp. Soc. Responsib. Environ. Manag.* **2026**, *33*, 5366–5382. [[CrossRef](#)]
67. Wang, X.; Gan, Y.; Zhou, S.; Wang, X. Digital technology adoption, absorptive capacity, CEO green experience and the quality of green innovation: Evidence from China. *Financ. Res. Lett.* **2024**, *63*, 105271. [[CrossRef](#)]
68. Zhao, C.; Wang, L. Artificial intelligence and enterprise green innovation: Evidence from a Quasi-Natural experiment in China. *Sustainability* **2025**, *17*, 2455. [[CrossRef](#)]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.