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Green Innovation Optimization for Climate Change ESG Business Readiness: Role of Generative AI in BRICS Countries

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ABSTRACT

Climate change introduces new challenges for businesses which require them to find ways to be resilient. Green innovations contribute to boost Environmental, Social, and Governance (ESG)-readiness leading to just transition without optimization. This study estimates the nonlinear effect of environmental innovation in ESG-readiness against climate change while allowing for the moderating role of citations from regenerative AI-research. We use BRICS countries to conduct the analyses with a machine learning based Panel-QARDL. We find that green innovations trace an inverted U-shaped effect and generative AI shifts this relationship upwards. Findings highlight the role of regenerative AI in boosting green innovation performance.

JEL Classification: M10, O32, Q55

1 | Introduction

Climate change reflects significant challenges globally. A significant portion is covered by BRICS countries (such as China, Russia, India, Brazil, and South Africa) that do not accept the challenges of climate change. These BRICS countries face unique opportunities and vulnerabilities through business readiness and adaptation strategies in addressing climate change. Several studies have suggested that business readiness for climate change is crucial for reducing climate-associated disasters in BRICS countries by improving and promoting sustainable economic growth through environmental technologies and international cooperation. Adaptation of nosiness models in BRICS countries is still a challenge. There should be a leverage trade agreement to adopt business models that cause minimal Carbon Dioxide (CO_2) emissions and to reduce climate pressure in BRICS countries (Martins 2019; Zamokuhle Mbandlwa. 2022). There is an adaptive capacity problem in developing countries including BRICS countries. They should adapt to managing climate change risk (Saeed et al. 2023; Sarkodie and Strezov 2019). All the BRICS countries have the potential to play a vital role in the governance of global climate by putting their collective efforts into activating global change and strengthening their power for better decision making (Petrone 2019). BRICS countries have agreed to international climate agreements, such as the Kyoto Protocol and the Paris Agreement, which target to balance environmental sustainability and economic growth (Kovalev and Porshneva 2021; Martins 2019). There are several challenges, both internal and external, within BRICS countries which include dependence on fossil fuels and barriers to adopting robust and modern strategies and climate change mitigation (Kovalev and Porshneva 2021). The world experienced a 121% growth in research in AI between 2017 and 2022 in which China and India leading the charts from BRICS countries (Emerging Technology Observatory 2024).

This study uses the ESG readiness data from (Chen et al. 2015) which is comprised of economic readiness measured by investment climate, governance readiness measured by stability of institutional arrangements to mitigate investment risks, and social readiness measured using social conditions to support efficient use of investments. The report by Chen et al. (2015) coins the sources of data used to measure this index. The data source includes World Bank Doing Business Reports, the World Bank Worldwide Governance Indicators Report, and the World Bank World Development Reports. Chen et al. (2015) provides the baseline score for each data to normalize the ESG readiness. A study by Ul-Durar et al. (2025) used this indicator as business sector readiness against climate change.

Use of generative AI can expedite patent development and reduce the cost and time barriers related to adoption (Masood et al. 2025; Ukoba et al. 2024). This technological facilitation is aligned with the just transition principle, allowing economic opportunities for all businesses towards sustainability. Generative AI can provide an enabling environment to adapt to environmental challenges (Bagiyam et al. 2024). There are several critical aspects of business readiness to climate change as a just transition. These companies are working efficiently and proactively to deal with climate related risks and not only mitigate potential financial losses but also be capable of starting new business ventures and opportunities in green environments. Use of AI helps in reducing the economic burden on vulnerable sectors during green transformation (Khan et al. 2024). A study by Bernard et al. (2025) highlighted that the use of the latest technologies, such as blockchain, leads to an increase in the environmental performance of firms.

Extreme weather is also a challenge due to an increase in carbon emissions. There are opportunities to start new businesses and shift customers' preferences towards sustainable products. If companies fail to adapt, it can lead to reputational damage and supply chain disruptions, therefore making it difficult for businesses to gain competitive advantages. A report by the Task Force on Climate-related Financial Disclosures (TCFD) explains the facts in detail (TCFD 2020).

The TCFD (2020) report highlighted unlocking financial value and enhancing long term resilience in the organizations by integrating climate risks into their strategic planning. Moreover, research from the Carbon Disclosure Project (CDP) (CDP 2019) explains that businesses equipped for climate risks often report stronger financial performance compared to their less equipped competitors (CDP 2019). Thus, climate change readiness is not only an ethical imperative but also a business necessity. Hence businesses are exploring the domain of just transition to combat climate change.

Business readiness to change in environmental difficulty is important in protecting short- and long-term stability and profitability. Extreme climate risk includes rising temperatures around the globe with significant financial and operational threats. For instance, the Global Risks Report 2020 ranked climate action failure as the top long-term global risk in terms of impact (World Economic Forum [WEF] 2020). Also, increased operational costs and regulatory penalties in companies due to the failure to adapt to climate change could face up to $1 trillion in financial risks, including disruptions to supply chains (CDP 2019). By using low carbon technologies and energy efficient practices in businesses that take part, climate readiness strategies can unlock opportunities worth nearly $2.1 trillion, particularly through innovation (Ellsmoor 2019).

1.1 | Environmental Patents and ESG Readiness

Environmental innovation presents itself as a potential source of enhanced readiness. In the domain of economic readiness, innovations can increase cost savings and market competitiveness. It can also shield businesses from volatile fossil fuel markets (Organization for Economic Co-operation and Development [OECD], 2024a, 2024b). Additionally, green innovations enable businesses to target environmentally conscious consumers (European Policy Center [EPC] 2011). Financial institutions are not providing discounted funding for sustainable initiatives that increase access to funds for green innovation (Bibi et al. 2024). These innovative approaches can develop climate-resilient infrastructure to minimize financial losses from floods and droughts (Ahmad et al. 2022).

Environmental innovations also enhance social readiness using reputation, stakeholder engagement, talent attraction, and community health. Green innovations help boost customer loyalty and brand equity (Scimita Group 2024). It attracts customers who attach value to consumption (Global Partner Solutions [GPSI] 2023). Environmental initiatives also come with collaborations among stakeholders such as communities, governments, and NGOs that build trust and goodwill and form a supportive network (Buscher and Spurling 2019). Financial innovations also help businesses in achieving sustainability (Cumming et al. 2024).

In the governance domain, environmental innovation can contribute to regulatory compliance and integrate ESG metrics for resilience. Innovations enable firms to comply with strict environmental regulations (Fan and Wu 2022) and develop ESG reporting frameworks (Gray Group International [GGI Insights] 2024) which, in turn, helps firms to be prepared for future climate scenarios and strengthen their corporate governance (Etty et al. 2022).

The green innovation and ESG readiness relationship are expected to exhibit nonlinear behaviour. Investments in green innovations such as energy-efficiency and renewable energy adoption can enhance ESG readiness (Long et al. 2023). However, the gains from green innovation may follow diminishing returns and exponential increases in development costs and uncertainties (Leyva-de la Hiz and Bolívar-Ramos 2022). The excessive focus on environmental patents may undermine ESG performance. Advanced technologies often come with high implementation costs and sophisticated infrastructure that strain financial resources (Mneimneh et al. 2023). This shows that research is needed to explore how financial management for green innovation transition is necessitated. Studies have shown that businesses need to optimize green innovation efforts (Liu 2024). This optimization requires financial management to prioritize investments in ventures that have the highest ESG impact (KPMG 2023). Robust models are required to prevent overexposure to high-cost/high-risk innovations (Khanchel et al. 2023). In a social context, overemphasis on technological solutions might reduce focus on human capital development and stakeholder engagement (Adisa et al. 2024). Similarly, from a governance perspective, economies with large environmental research portfolios could face increased complexities and transparency challenges (Underdal 2010). All these aspects indicate that a balanced approach is required with environmental patents so that firms can maximize climate change resilience.

1.2 | Generative AI and ESG Readiness

The evolution of generative AI (Artificial Intelligence) has revolutionized the way humans perceive complicated tasks. Businesses have now integrated generative AI into their processes to gain a competitive advantage. Generative AI constitutes advanced algorithms that are capable of synthesizing data-driven solutions, automating operations, and enabling effective decisions. GenAI can develop targeted content on emerging global risks while keeping an eye on local context, which led to its increased adoption (Yap and Moyer 2024). This automative decision making can help businesses to optimize resource management and support sustainability initiatives (Apotheker et al. 2024; Pransky and Knickle 2024; Relyea et al. 2024). Businesses can leverage generative AI to improve productivity and substantially reduce costs by putting them on track to finance for environmental concerns abatement. Its applications include resource management optimization, smart financial modelling, bringing sustainability, and improving economic, social and governance (ESG) readiness (Balcıoğlu et al. 2024; Borah 2023; Feiner et al. 2024; Webster and Hussam 2024). GenAI can help SMEs in China ensure that their supply chains comply with sustainable development goals (Wang and Zhang 2025). GenAI has also helped in the development and undertaking of decarbonization efforts (PricewaterhouseCoopers [PwC] 2024).

Conventional AI models were basically designed for pattern recognition and prediction whereas Generative AI models supersede them by automating complex data driven solutions (Harrington 2024) which makes it suitable to handle uncertain environments. Generative AI is designed to support innovative solutions by synthesizing complex decision models (Alasadi and Baiz 2023). The advent of generative AI has also raised questions about the ethical implications, which require AI governance frameworks to ensure data privacy and regulatory compliance (Chien 2024; Vohra 2023). However, this inclusion of generative AI has fostered social readiness in organizations by promoting workforce resilience and streamlining corporate social responsibility challenges. Using complex data analysis, generative AI empowers businesses to assess employee engagement and performance while staying within the social context (Bruce 2024; Thomas 2023). The integration of generative AI requires a balanced approach to address consequential job displacements (Balcıoğlu et al. 2024).

The emerging transformative force of generative AI can help boost the economic readiness of businesses by automating processes and increasing productivity. Generative AI can help reduce the time taken to find solutions and improve overall operational efficiency. Generative AI investments have seen a significant decrease in cost and an increase in revenue to ensure the competitive advantage of businesses (Apotheker et al. 2024; Relyea et al. 2024). Resource management optimization is one of the key traits of generative AI. It can increase raw material yields and minimize waste production. This not only has an environmental impact but makes business economically viable to achieve sustainability (Balcıoğlu et al. 2024; Feiner et al. 2024). Generative AI assists in financial modelling with a special context for renewable energy. AI-driven tools can automate complex financial modelling and provide scenario planning amid climate change (Terra 2024; Webster and Hussam 2024). It can also detect anomalies in the data and can conduct rapid analysis which increases corporate due diligence and investments related to climate change (Bakkali et al. 2024). Furthermore, generative AI can provide forecasts by linking innovative solutions with financial returns (Business for Social Responsibility [BSR] 2024).

Generative AI can enhance social readiness in businesses by improving the resilience of the workforce. It makes complex data actionable which eases organizations' informed decisions. Generative AI can help in assessing employee well-being, which is linked with a 55% increase in firm performance (Thomas 2023). Generative AI can identify the stress points of employees by analysing psychosocial factors. This enables the motivational and behavioural drive for performance (Thomas 2023). Generative AI can help in Corporate Social Responsibility (CSR) by improving engagement with stakeholders (Vohra 2023). AI can develop educational tools to increase technology adoption in the workforce (Thomas 2023). Generative AI can propose innovative sustainability initiatives that businesses can leverage to drive societal and environmental gains using a collective approach (Bruce 2024).

Generative AI plays a pivotal role in enhancing governance readiness within businesses with special context to climate change response and sustainable development goals (DiBianca 2024). Organizations with centralized AI governance can help oversee AI adoption, leading to achieving a competitive advantage. Hence, GenAI can help in energy efficiency, waste reduction and sustainable product development thus leading to improved ESG performance (TheCodeWork Team 2024).

The evolution of generative AI starts with academic research to explore the potential in many fields. The first impact of academic adoption of generative AI is that it leads to an increase in research productivity and democratization of complex analytical processes (Perkins and Roe 2024). Generative AI is a seismic shift in research; it has been used to explore protein structures, drug design and material sciences (Liu and Jagadish 2024). Research in generative AI has revolutionized simulation and predictive modelling in assessing signals from data, which has applications in climate scenario modeling (Sengar et al. 2024). Generative AI research has shown its potency in nonlinear internalization for international businesses. It contributes in faster literature, data synthesis (Vissak and Torkkeli 2025), and research dissemination (Ganguly et al. 2025). A study by Luo et al. (2024) assessed the role of AI research publications in 20 countries and showed that AI research has contributed to improving business sector productivity. An increase in AI publications and their citations usually gains the attention of industries as a collaborative partner which can help bridge the gap between industry and academia (Färber and Tampakis 2024).

Considering the potential of generative AI, there are still several operational challenges that organizations must navigate to gain advantage. There are legal considerations surrounding AI implementation when complying to regulations (Chien 2024).

Conclusively, generative AI has a unique transformative ability for businesses in not only addressing economic performance but also aligning sustainability goals. By using generative AI organizations can test similar complex decisions and establish effective risk management in addressing climate change challenges (Chien 2024; DiBianca 2024). This study seeks to explore how research in generative AI has led to changes in the economic, social, and governance readiness of businesses against climate change.

The research gap emerges from the limited understanding of the adaptability of generative AI as a transformative force which helps in contextual alignment of innovations with climate change resilience. According to Aharah (2024) adopting GenAI is necessary to meet ESG goals. This study adds to the literature explaining how generative AI can improve the innovation performance as evident from a study on manufacturing firms in China (Jing and Zhang 2024). This study also demonstrated the application of machine learning models of dynamic panel data for which literature is scarce.

This study initially explores the nonlinear role of environmental innovation on the ESG readiness for Brazil, Russia, India, China, and South Africa (BRICS countries). BRICS countries are a diverse group of emerging economies with their own industrial, economic, and environmental challenges. They have the potential to lead global climate change initiatives (TV BRICS 2024). This study further uses the citation count from generative AI research publications as an indicator of the intensity of generative AI as a moderator to the environmental innovation and ESG readiness relationship. It's higher citation could indicate influence, maturity and reliability of generative AI research in practical implementation (Apotheker et al. 2024; Balcıoğlu et al. 2024).

Figure 1 provides the clustering of the ESG and EPAT relationship across countries. It highlights the debate at hand whereby some BRICS countries are experiencing a positive relationship between environmental innovation and ESG while others have a negative relationship. While the average value of generative AI citations is mentioned in the legend, the visual inspection provides inconclusive patterns between these three variables other than the fact that, on average, the scatter points are higher for countries with higher citations. An in-depth relationship assessment is needed.

This study uses an innovative methodology that is robust in econometrics while leveraging data science tools to improve predictive performance. The long and short run estimates of quantile ARDL regression are estimated within the machine learning framework which helps to address the most common data related challenges relevant to the selected sample.

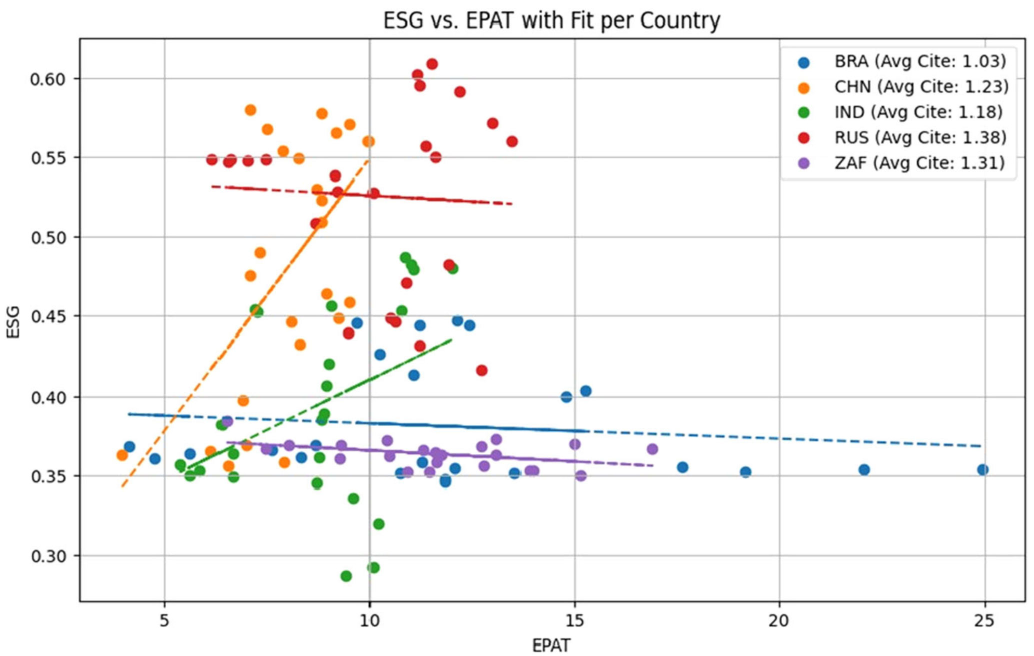

FIGURE 1 | Linking Environmental Patents with ESG readiness. *Note:* This is a scatterplot with colour clustering and linear fit based on the BRICS countries in the sample with average value of moderator provided in the legend. *Source:* Author Self Constructed. [Color figure can be viewed at wileyonlinelibrary.com]

Following the introduction, this study provides a literature review in Section 2. The methods are discussed in Section 3 building up to the results and discussions in Section 4. The study is concluded and discusses policy implications in Section 5.

2 | Literature Review

2.1 | Theoretical Review

The foundation model of the study is that there is a nonlinear effect of green innovation on ESG readiness whereby, at initial levels of innovation, firms experience increased operational efficiency and environmental commitment (Porter and Linde 1995). The Knowledge-Based View supports this positive effect whereby firms increase their absorptive capacity to integrate sustainable practices (Cohen and Levinthal 2000). However, this trajectory is not static, with the trajectory changes after optimal threshold leading to diminishing returns on green investments. This is because increased investments would lead to increased complexity in multiple and overlapping environmental improvements (Berrone et al. 2013). The Resource Based View also explains this turning point where resources meet constraints from organizational capabilities. Here excessive innovation may strain organizational capacity and form coordination challenges (Russo & Fouts. 2017). Excessive innovation may also be perceived as greenwashing rather than genuine commitment that may reduce ESG effectiveness (Delmas and Burbano 2011). This calls for finding the optimal level of green innovation corresponding to organizational capacity of the business (Xie et al. 2019).

This study proposes that the research in generative AI can augment the performance of green innovation in relation to the ESG readiness of businesses. The theoretical foundations originate from the Resource Based View (RBV) advocating generative AI as a valuable and imitable resource that can increase efficiency or reduce the cost of innovations (Krakowski et al. 2023). GenAI improves decision making, creativity, and problem-solving capabilities starting from the complex and frontier domains. It has shown its fruits in the United States of America (USA) and China (Acharya and Dunn 2022). GenAI enables rapid prototyping, simulation, and optimization of sustainable solutions. It can synthesize novel designs, simulate complex environmental scenarios, and optimize resources to accelerate green innovation (Ding et al. 2024).

Furthermore, the Dynamic Capabilities Theory positions generative AI as an enabler to reconfigure green innovations in response to climate change challenges (Sjödin et al. 2023). GenAI fosters continuous and automated experimentation which can help in refining sustainable technologies. It can maximize green innovation spillovers and diffusion (Oliveira and Trento 2025). Joined together, the Knowledge Based View also supports the foundation model that generative AI can help businesses to absorb, process and apply innovations effectively (Ruchit Parekh and Sophia Wright 2024). Conclusively, this study proposes that GenAI can help organizations to get more out of green innovations which are constrained by organizational capacity using its transformational capability (Panyam 2024).

2.2 | Empirical Review

Evolving consumer expectations for sustainability in companies prepared for climate change also tend to have a competitive edge by reducing their carbon footprint, enhancing brand reputation, and meeting ethical requirements (Woetzel et al. 2020). Environmental uncertainties are a great challenge to manage climate readiness which should show a pathway to business resilience and growth. Literature has coined the business transformative impact of generative AI. In the context of projections and simulations, it has contributed significantly. Studies have shown that AI can reduce resource and energy intensity in improving environmental governance (Nishant et al. 2020). AI is critical for developing urban climate change adaptation strategies as it can assess the context and include collaborative partners to abate regional vulnerabilities (Srivastava and Maity 2023). Artificial Intelligence creates an awareness and understanding of climate change to abate the climate crises effectively. It is also effective for the reduction of carbon footprints (Cowls et al. 2023). AI can drive sustainable business models which can link economic goals with SDGs. It can help to develop knowledge management systems that can assist in the adoption of SDG targets (Di Vaio et al. 2020). Open-access generative tools like ChatGPT can automate and improve data analysis for decision making related to risk management (Chen et al. 2023). AI can detect minute changes in data to understand climate patterns, which enables businesses to predict extreme events (Satish et al. 2023). Artificial Intelligence is transforming data from unstructured to structured, impactful decision making and rule enforcement in the face of climate change (Scoville et al. 2021).

Climate change is directly aligned with business readiness (BSDC 2017), especially SDG 13: Climate Action. According to the Paris Agreement, which aims to control and achieve the targets of global warming to below 2°C, this is needed for businesses to reduce carbon emissions and to mitigate climate risk. The UN evaluations report says that fulfilling the SDGs could generate new opportunities worth $12 trillion by 2023, particularly in sectors like food, cities, and energy that are heavily impacted by climate change (Business & Sustainable Development Commission [BSDC] 2017).

Access to the internet has also increased the ability of businesses to abate climate change challenges. The Internet has influenced businesses' adaptive capacity by formulating effective policies and strategies. The Internet has enabled several technological advancements like the Internet of Things (IoT) to boost knowledge exchange between technical and policy communities (Carr and Lesniewska 2020). The Internet also drives technological innovation related to environmental pollution (Ren et al. 2023).

Green technology is also critical for boosting business readiness. Patents can increase the development and dissemination of technologies to mitigate climate change. Literature has pointed to it as a strong initiative to mitigate climate change (Raiser et al. 2017). Green technology can improve efficiency, waste reduction, and cost management (Alves de Lima et al. 2013; Khan and Singh 2023). The response of businesses to climate change improves with the adoption of green patents (Su and

Moaniba 2017). However, a study in China has shown mixed results of green patents on carbon reduction mostly due to financial constraints (Chen et al. 2021).

Firm investment is one of the important components that drives firms' ESG readiness for climate change. Governments can provide access to finance which can enable businesses to invest in new ventures (Owen et al. 2018). Firm investments represent private sector engagement in climate resilience technology development (Biagini and Miller 2013).

Empirical studies mostly have a theoretical focus on assessing the effects of AI. Surveys show that generative AI investments are expected to be higher than conventional AI where a 10% return on investment is expected (Marshall et al. 2024). This study uses the data of generative AI research citations as an indicator of the adoption of generative AI at national level, especially by academia. The adoption at an academic level indicates that AI learned human capital will be developed, which will help in the transition towards AI adoption in industry (Barros et al. 2023; Liu and Jagadish 2024). Since AI adoption may require time to show its impact, this study has used the quadratic transformation of generative AI research and citation while using environmental patents as a moderator. While focusing on the generative AI abilities, it shows higher accuracy in climate related predictions. Machine learning and big data tools can provide reliable forecasts (Cowls et al. 2023; LC and Tang 2024). Generative AI can help industries to achieve Industry 5.0 along with SDG goals (Ghobakhloo et al. 2024). Its integration can help in achieving social sustainability (Al-Emran et al. 2024). Generative AI has the potential to augment human creativity and transcend the innovation process (Pan 2024). It can work as a collaborator in developing business models, processes, and values (Sedkaoui and Benaichouba 2024). The cost of prototyping is significantly reduced when innovation is linked with generative AI (Bilgram and Laarmann 2023). It also improved efficiency and cost reduction in business and finance (Chen et al. 2023). More importantly for mangers, generative AI leads to accelerated product development and reduced time-to-market (Paliwal et al. 2024). This led to the development of the first set of hypotheses:

H1. *Green innovation boosts ESG readiness of businesses but follows diminishing returns.*

H2. *Generative AI positively moderates the green innovation and ESG readiness relationship.*

H3. *Access to the internet positively affects ESG readiness.*

H4. *Firm capitalization positively affects ESG readiness.*

With regard to further studies in the domain of strategic management, there are several studies which have used complex econometric models but most have overlooked the use of models that are deployment ready and leveraging data science.

3 | Methods

This study has used the data of BRICS countries from 2000 to 2023. The variables used in the study are mentioned in Table 1. ESG readiness is the dependent variable, which assesses how ready businesses are in funding for climate change. This data is compiled by the Notre Dame institute. These include investment climate as an economic factor, stable institutional arrangements as a governance factor, and social conditions as a

TABLE 1 | Variables and data sources.

Variable name (symbol)	Definition	Source
Economic, Social, and Governance Readiness (ESG)	Firms' economic, social and governance readiness to invest for climate change abatement	C. Chen et al. (2015)
Internet Access (INT)	Proportion of population who have access to the internet	WDI (2021)
Firm Investment (GFCF)	Gross fixed capital formation as percent of GDP	WDI (2021)
Environmental Patents (EPAT)	Patents related to renewable energy or increasing efficiency of nonrenewable energy	OECD (2024a)
Relative Generative AI citations (CITE)	Proportion of citations received from generative AI research	OECD (2024b)

TABLE 2 | Descriptive stats.

Stats	ESG	CITE	PUB	EPAT	INT	GFCF
Mean	42.96	1.22	1.33	10.10	37.94	24.43
Median	40.17	0.96	1.12	9.58	36.3	21.37
Sd	8.32	1.13	0.93	3.28	38.63	9.53
Skewness	0.58	4.15	4.03	1.36	0.22	0.69
Kurtosis	2.03	26.37	27.21	6.83	1.61	2.08

TABLE 3 | Correlation matrix.

Correlations						
ESG	1.00					
CITE	0.05	1.00				
PUB	-0.29	0.25	1.00			
EPAT	-0.13	-0.04	-0.21	1.00		
INT	0.31	-0.36	-0.56	0.29	1.00	
GFCF	0.37	0.002	-0.03	-0.43	-0.15	1.00

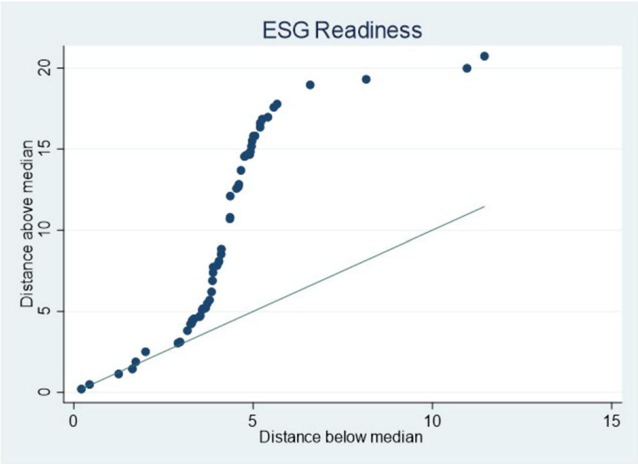

FIGURE 2 | Symmetry plot of dependent variable. *Note:* This is a median distance plot that detects non-normality if the scatter points deviate away from the line. *Source:* Author Self Constructed. [Color figure can be viewed at wileyonlinelibrary.com]

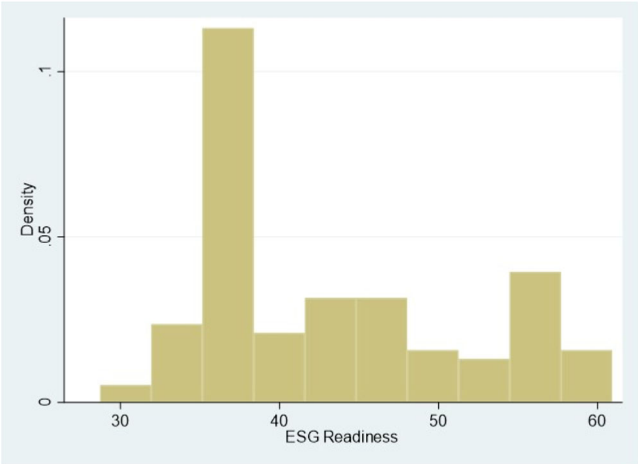

FIGURE 4 | Histogram of dependent variable. *Note:* This is a histogram plot which displays the skewness and kurtosis and consequently shows normality status of the data. *Source:* Author Self Constructed. [Color figure can be viewed at wileyonlinelibrary.com]

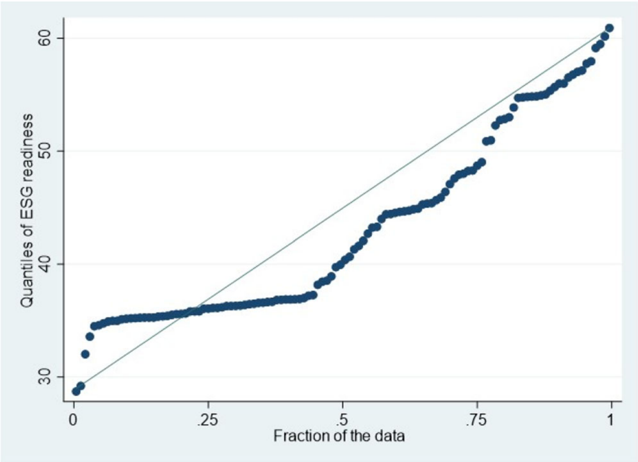

FIGURE 3 | Quantiles plot of dependent variable. *Note:* This is the quantile distance plot which detects non-normality if the scatter points deviate away from the line. *Source:* Author Self Constructed. [Color figure can be viewed at wileyonlinelibrary.com]

social indicator. The control variables include access to the Internet and firm investments. The main independent variables are green innovation as instruments for generative AI adoption at national level and are used as a moderator.

The AI citations data is compiled using the citation proportion where by the citations are split proportionally to each country from which authors are in the publications (Emerging Technology Observatory 2024; OECD 2024b). OECD (2024b) methodology note also acknowledges that the data of citations estimate quality of AI publications after including a decay factor. Citations in AI-related research publications are used as a meaningful indicator of AI technology adoption as an early signal of knowledge diffusion before commercial deployment. Citations are not merely of academic interest but the foundational knowledge is also necessary for industrial application. The citations are outcome of research produced by universities that are knowledge-producing centres that facilitate technology development, testing, and transfer via industry collaborations. Hunt et al. (2024) highlighted that the AI hotspots are not defined because of the number of patents they produce but rather AI publications being the main factor. The research papers in AI are more contributory to spreading AI jobs.

Following is the estimation equation of the study which includes the quadratic effect and a moderator assessed using Haans et al. (2015) framework. This study explains the theoretical foundation of using quadratic and moderators in the estimation equation. It also provides guidance on how to interpret such complex relationships. According to this study, if both positive and negative effects simultaneously exist between variables, then it can lead to a U or inverted-U shaped nonlinear effect. For this, the literature review discussed the debate of positive and negative effects of environmental patents on ESG readiness. The quadratic moderation is visualized using the template provided by Dawson (2013) which uses the slope coefficients and mean and standard deviation of independent variables to visualize the curvature of effects.

This study has used panel data to address differences in countries and used quantile regression to address non-normal variables. Since the number of years per country is more than 19, this study assumes that the data could be nonstationary in nature (Pedroni 2008). This study has used several panel unit root tests to assess the nature of the variables. The tests include the LLC (Levin et al. 2002), IPS (Im et al. 2003), Fisher Augmented Dickey Fuller (ADF), and Phillip and Perron (PP) (Maddala and Wu 1999) tests. According to time series econometrics if any one of the variables is non stationary then standard static ordinary least square based regression (Fixed and Random effect models) can provide spurious results (Enders 2015). For robust estimates, the selected variables (if they have at least one nonstationary variable) must be cointegrated. This study has also applied the panel cointegration test provided by Kao (1999). The presence of cointegration indicates that the selected variables are related in the long run while there might be some fluctuations in the short run and the rate at which the model is converged from short run to long run is estimated using the convergence coefficient (Quintos 1998). This study has used a two – step Error Correction Model method to estimate long run effects in isolation and then used its residuals as an independent variable it its first lag form (Enders 2015).

FIGURE 5 | Model outliers. *Note:* It is an outlier fence plot using EViews which detects the presence of outliers in the data making data non-normal. *Source:* Author Self Constructed. [Color figure can be viewed at wileyonlinelibrary.com]

This study adapted the ARDL model within panel quantile regression to account for nonstationary variables (Blackburne and Frank 2007; Pesaran and Smith 1995). This Panel ARDL model is suitable even when the variables are mixed order of integration (Pesaran and Smith 1995). This estimation model has previously been used by Arshed (2023) and Arshed et al. (2022) to estimate the long term effect of independent variables

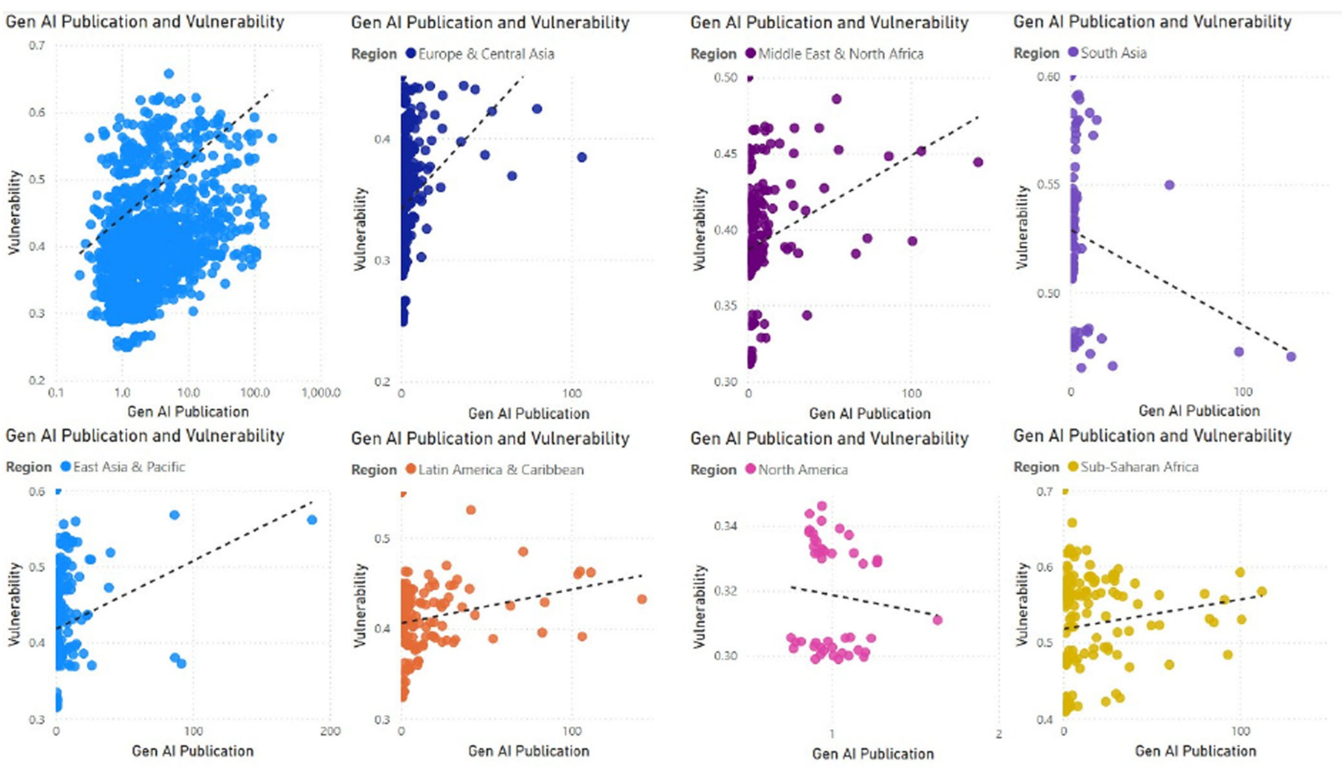

FIGURE 6 | Global Incidence of generative AI and Climate change vulnerability. *Note:* This is a region wise scatter plot showing the heterogeneity in association between GenAI and Vulnerability to climate change. *Source:* Author Self Constructed. [Color figure can be viewed at wileyonlinelibrary.com]

on dependent variables. This study has used the Dynamic Fixed Effect specification of Panel ARDL model.

This model is further estimated within the machine learning framework which leverages data-driven optimization. The standard machine learning algorithms to estimate relationships like linear regression, logistic regression, naïve Bayes, and Autoregressive Integrated Moving Average (ARIMA) models require the data to be normally distributed for machine learning assessment. This study has used the quantile regression method which is robust to outliers and can be used for non-normal data. The last year of each country is used as a testing sample for validity assessment. This nonrandom splitting of sample will solve temporal leakage of data (Cerqua et al. 2024).

Machine learning methodologies supersede standard econometric methodology in several ways. Machine learning can capture the complexity of the data (Varian 2014), and manage high dimension data which has high collinearity (Assistance 2018; Li and Kockelman 2021). These models have higher predictive performance using cross-validation and hyperparameter tuning ensuring robust predictions (Merler 2018). Unlike the focus on model building of econometric models, machine learning models also provide easy automation and scalability to streamline decision tasks (Fawy 2023). However, this study has used the transformed quantile regression which is exploiting the advantages of machine learning models as well as econometrics.

The quantile regression generalizes the conditional quantiles of the response variable rather than the mean in regression. Therefore, for a given quantile τ, the model estimates the conditional distribution as:

$$Q_\tau(Y|X) = X\beta_\tau. \tag{1}$$

The quantile regression minimizes the loss function for a given τ where $\mu = y - X\beta$.

$$\rho_\tau(\mu) = \mu(\tau - I(\mu < 0)). \tag{2}$$

Based on that the objective function for the quantile regression to estimate the slopes is the following:

$$\hat{\beta}_\tau = arg \min_{\beta} \sum_{i=1}^{n} \rho_\tau\left(y_i - X_i\beta\right). \tag{3}$$

Conclusively, this model is robust in handling heteroskedasticity, autocorrelation, mis-specification, and non-normality (Meinshausen 2006) while, because of machine learning, the model is more efficient and provides assessment in terms of its learning and forecasting performance (Chen 2021).

$$\begin{aligned} ESG_{\tau it} = {} & \alpha_{\tau 1} + \alpha_{\tau 2} EPAT_{it} + \alpha_{\tau 3} EPAT_{it}^2 + \alpha_{\tau 4} CITE{*}EPAT_{it} \\ & + \alpha_{\tau 5} INT_{it} + \alpha_{\tau 6} GFCF_{it} + e_{\tau it}, \end{aligned} \tag{4}$$

$$\begin{aligned} \Delta ESG_{\tau it} = {} & \alpha_{\tau i1} + \alpha_{\tau 2} \Delta EPAT_{it} + \alpha_{\tau 3} \Delta EPAT_{it}^2 \\ & + \alpha_{\tau 4} \Delta CITE{*}\Delta EPAT_{it} + \alpha_{\tau 5} \Delta INT_{it} \\ & + \alpha_{\tau 6} \Delta GFCF_{it} + \delta_\tau ecm_{it-1} + e_{\tau it}. \end{aligned} \tag{5}$$

TABLE 4 | Panel unit root tests.

Tests (Prob.)	ESG	ΔESG	CITE	PUB	INT	ΔINT	GFCF	ΔGFCF	EPAT	ΔEPAT
LLC Test	−0.56 (0.29)	−5.34 (0.00)*	−1.82 (0.03)*	−8.27 (0.00)*	−1.44 (0.07)*	−0.18 (0.42)	−1.96 (0.02)*	−3.86 (0.00)*	0.27 (0.61)	−3.03 (0.00)*
IPS Test	−0.55 (0.29)	−3.65 (0.00)*	−1.46 (0.07)*	−5.62 (0.00)*	1.88 (0.97)	−1.53 (0.06)*	−1.32 (0.09)*	−3.75 (0.00)*	0.46 (0.67)	−5.14 (0.00)*
Fisher ADF	9.67 (0.46)	31.23 (0.00)*	17.10 (0.07)*	52.66 (0.00)*	3.89 (0.95)	18.38 (0.04)*	14.65 (0.14)	32.58 (0.00)*	8.97 (0.53)	45.10 (0.00)*
Fisher PP	9.77 (0.46)	62.73 (0.00)*	44.29 (0.00)*	18.15 (0.05)*	3.61 (0.96)	31.20 (0.00)*	15.08 (0.13)	45.72 (0.00)*	21.27 (0.02)*	111.2 (0.00)*

*Significant at 10%.

4 | Results and Discussions

Table 2 provides the descriptive statistics of the variables used in the study. Here it can be seen that all the variables are non-normal in nature, evidenced from non-equality of mean and median, having skewness and kurtosis. Other than internet access, all the variables have mean values higher than standard deviation which makes them under-dispersed while internet access is over-dispersed. Table 3 provides the correlation between the variables. Here it can be noted that since none of the independent variables has a high pairwise correlation with other independent variable this rules out the likelihood of multicollinearity in the data (Arshed 2020; Gujarati 2009).

Figure 2 is the median distance plot, Figure 3 is the quantiles distance plot, and Figure 4 is the histogram, all of which provide a graphical assessment of the normality of the data. Here it presents the evidence that the data is non-normal with thick tails. Simple least square based estimation would not be able to provide an accurate inference (Arshed 2020). The estimation of quantile regression helps to provide outlier robust estimates along with estimates at different distributional positions in the data (Koenker 2005). Figure 5 is the outlier fences plot which further addresses the detection of outliers in the data. There are some observations which are beyond Tukey fences indicating that there is a presence of outliers.

Figure 6 presents the association between generative AI research and climate change vulnerability across different regional groups using scatter plot and linear fit. Here the overall increase in generative AI leads to an increase in vulnerability but it has a negative association in regions like North America and South Asia.

TABLE 5 | Panel cointegration test.

Cointegration test	Test value (Prob.)
KAO ADF test	3.95 (0.00)*

*Significant at 10%.

Table 4 provides the outcome of panel unit root tests using LLC, IPS, Fisher ADF, and PP test. Here variables like CITE and PUB are only tested to the level form as it is confirmed to be $I(0)$ in nature. While other variables like ESG, INT, GFCF, and EPAT are $I(1)$ in nature. Table 5 provides the KAO panel cointegration test where the significant test value confirms the long run relation between the variables in the panel data setup.

Table 6 provides long estimates of the regression equation using panel quantile ARDL model estimated using a machine learning framework. The last year of each country is excluded from the training sample for testing purposes. The machine learning evaluation provided the Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). Since RMSE is less than 10% of the mean of dependent variable, this shows that the model has been able to predict the changes in the dependent variable (ESG) significantly. Further, the R-squared estimates show that at the median the selected variables are able to explain 23% of the variation in the ESG. Figure 7 visualizes the forecasting performance whereby the forecasting incidences (green dots) are located around the perfect prediction line. The estimates of panel quantile regression are shown for quantile 25, 50, and 75, respectively and these estimates are also plotted in Figure 8 where the coefficient value is on the y axis and the quantile positions of dependent variables are on the x axis. Figure 9 is the prediction performance of the model across the sample countries. It shows that the long run model has been able to underpredict Brazil, China, and Russia while it has overpredicted India and South Africa. This indicates that, based on the selected model, the ESG readiness will tend to increase in India and South Africa while it will decrease in the case of other countries.

The results of long run estimates show that a 1% increase in internet access leads to an increase in ESG readiness by 0.001%. This finding is aligned with the theoretical notion that digital inclusion fosters knowledge sharing and technology adoption for sustainability. Thus enhanced communication flow enables firms to implement ESG promoting strategies (Gupta 2021). This digital inclusion can help increase in efficiency of IoTs that can optimize resource use (Gupta 2021).

TABLE 6 | Panel quantile ARDL estimates.

Variables	Coefficients at 25 percentile	Coefficients at 50 percentile	Coefficients at 75 percentile
EPAT	0.035 (0.00)***	0.043 (0.00)***	0.054 (0.00)***
$EPAT^2$	−0.001 (0.00)***	−0.002 (0.00)***	−0.002 (0.00)***
CITE × EPAT	0.002 (0.00)***	0.001 (0.06)*	0.001 (0.25)
INTE	0.001 (0.02)**	0.001 (0.00)***	0.002 (0.00)***
GFCF	0.005 (0.00)***	0.005 (0.00)***	0.004 (0.00)***
Pseudo R^2	0.066	0.229	0.261
Machine learning evaluation			
MSE	0.02	0.02	0.03
RMSE	0.14	0.13	0.16
MAPE	0.16	0.16	0.33

*Significant at 10%.
**Significant at 5%.
***Significant at 1%.

Similarly, a 1% increase in firm investment leads to an increase in ESG readiness by 0.005%. This shows that a higher level of firm investment helps businesses to become resilient to climate change (Gao and Krol 2022). Higher investments build the required infrastructure (physical and digital) that can enable firms to be resilient.

The coefficient of EPAT is positive while EPAT squared is negative showing the increase in environmental patents have an inverted U-shaped effect on the ESG readiness. This shape depicts the presence of the law of diminishing returns in terms of the effect of environmental innovation of ESG readiness (Eaton Business School [EBS] 2024; Zhang et al. 2023). This is

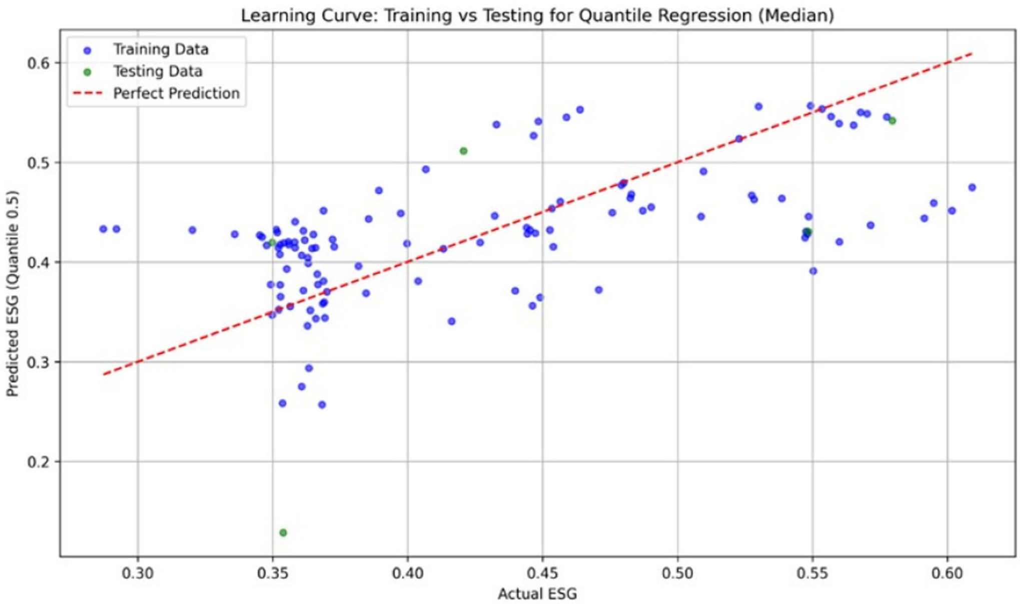

FIGURE 7 | Model prediction performance. *Note:* This is the learning curve showing the differences in actual and predicted dependent variable. Here, proximity to the red line shows quality of prediction performance. *Source:* Author Self Constructed. [Color figure can be viewed at wileyonlinelibrary.com]

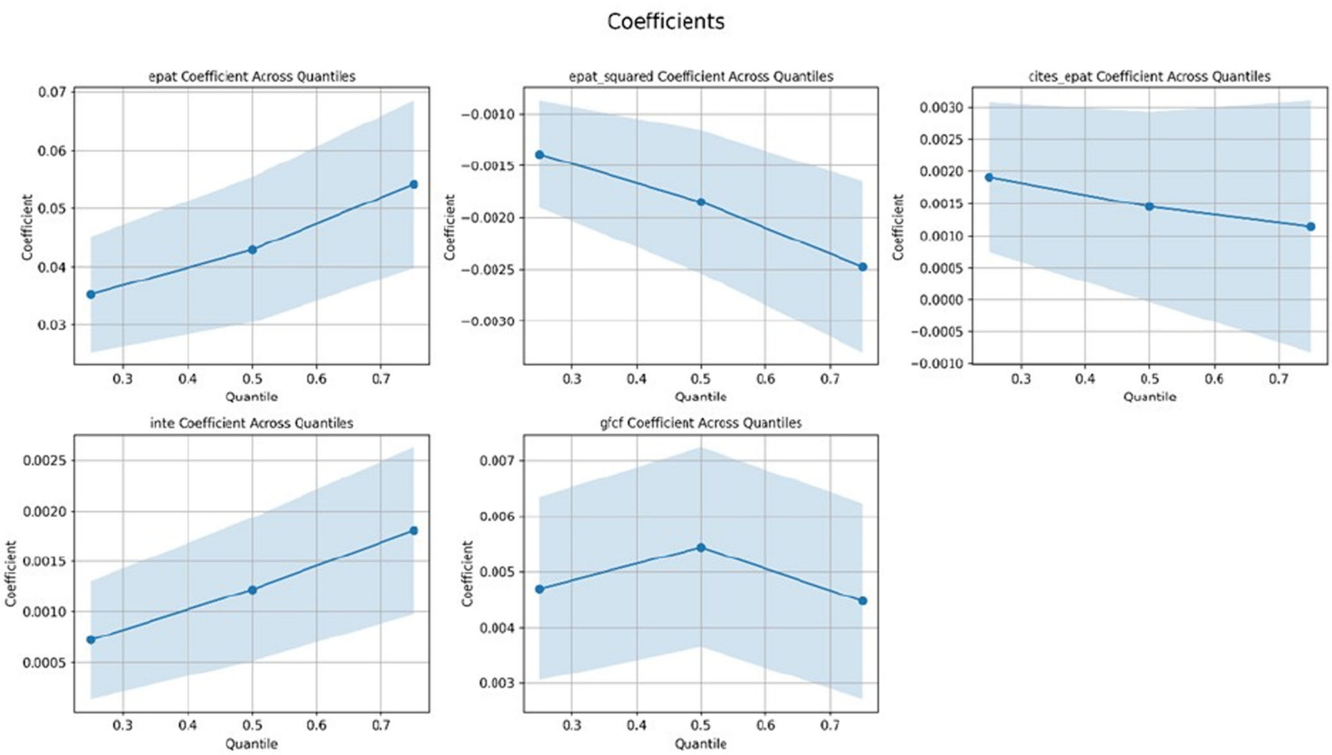

FIGURE 8 | Quantile-wise long run estimates. *Note:* This is a line plot showing the slope coefficients at three percentile (25, 50, and 75) positions. *Source:* Author Self Constructed. [Color figure can be viewed at wileyonlinelibrary.com]

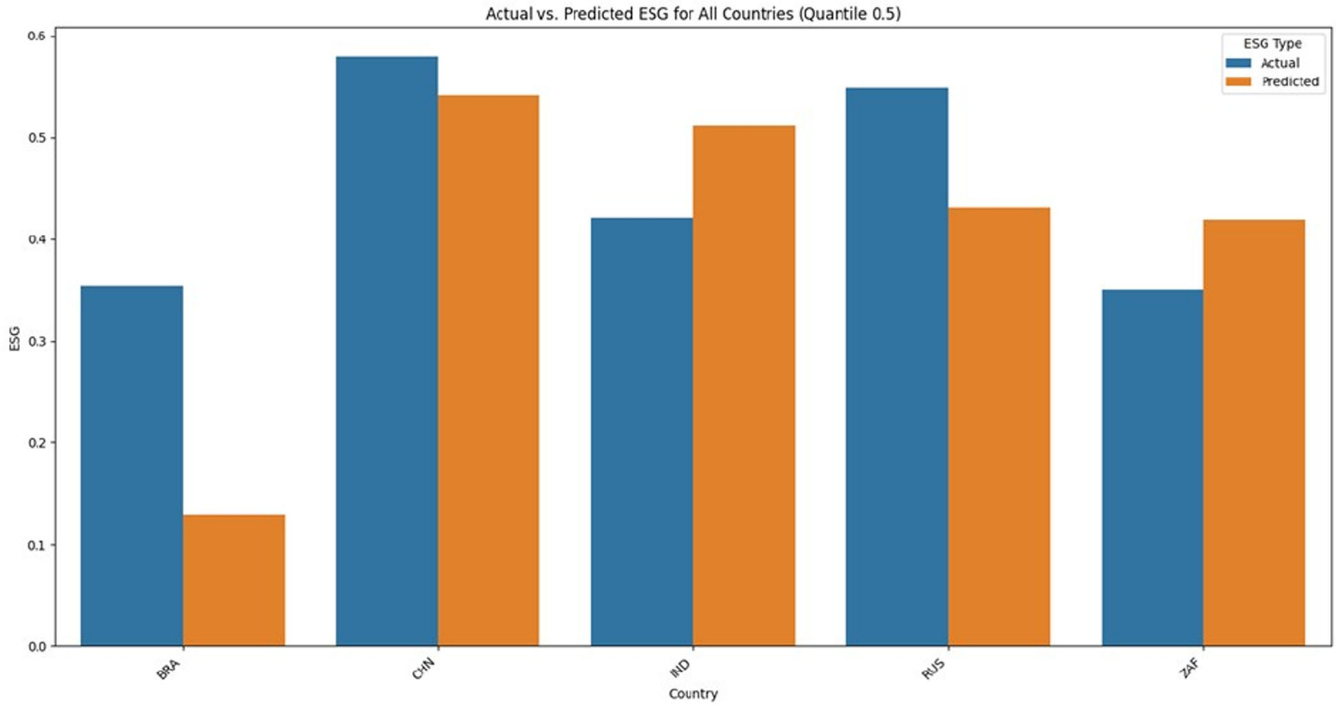

FIGURE 9 | Country wise prediction performance. *Note:* This is the column chart showing the country wise difference between actual and predicted dependent variable at medians. *Source:* Author Self Constructed. [Color figure can be viewed at wileyonlinelibrary.com]

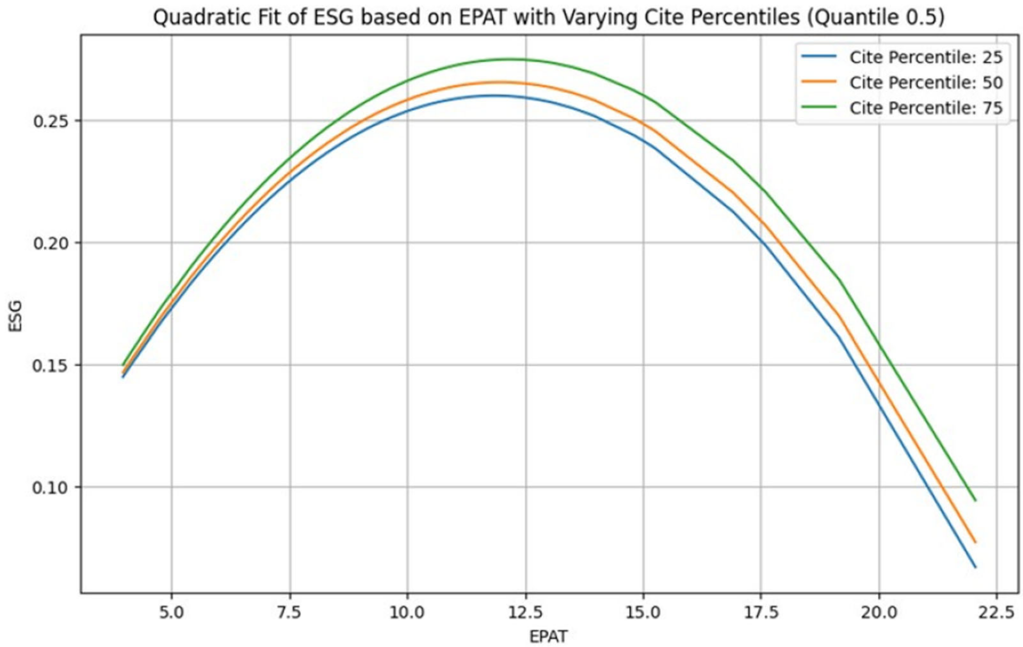

FIGURE 10 | Projection of quadratic effects with moderation. *Note:* This is the line chart showing the projection of quadratic effect moderated by GenAI at three different quantile positions. *Source:* Author Self Constructed. [Color figure can be viewed at wileyonlinelibrary.com]

also explained by the fact that excessive innovation accumulation leads to rigidity and inflexibility in dynamic reconfiguration because of technological complexity (Cohen et al. 2023; Xuhua et al. 2023). Here CITE is a number of citations from generative AI research publications. It has a positive moderating effect on the EPAT–ESG relationship which shifts the inverted U-shaped curve upwards (Figure 10). This advocates that extensive research in generative AI can help increase the effectiveness of EPAT. This is because it can enhance research efficiency, optimize resource allocation, and facilitate collaboration among industries.

Table 7 provides the short run quantile ARDL estimates. The coefficient of ECM_{-1} is negative and significant for quantiles 25 and 50 in the short run showing that the overall model is converging. Policy makers can intervene using the independent

TABLE 7 | Short run estimates of panel quantile ARDL.

Variables	Coefficients at 25 percentile	Coefficients at 50 percentile	Coefficients at 75 percentile
ΔEPAT	−0.001 (0.789)	0.002 (0.529)	0.0005 (0.901)
$\Delta EPAT^2$	0.000 (0.996)	−0.0001 (0.400)	0.000 (0.755)
ΔCITE × ΔEPAT	0.000 (0.423)	0.000 (0.906)	0.000 (0.569)
ΔINTE	0.000 (0.866)	0.0005 (0.192)	0.0003 (0.588)
ΔGFCF	0.001 (0.318)	0.0005 (0.620)	−0.0003 (0.749)
ECM_{-1}	−0.056 (0.046)**	−0.063 (0.020)**	−0.045 (0.133)
China	0.005 (0.177)	0.004 (0.277)	0.009 (0.070)*
India	0.003 (0.399)	0.001 (0.870)	0.003 (0.507)
Russia	0.011 (0.015)**	0.012 (0.012)**	0.014 (0.026)**
South Africa	−0.002 (0.700)	−0.006 (0.115)	−0.008 (0.108)
C	−0.002 (0.604)	0.001 (0.700)	0.005 (0.216)
Pseudo R^2	0.061	0.088	0.101

*Significant at 10%.
**Significant at 5%.

variables to influence the ESG readiness. While most of the variables are insignificant except for the country dummies like Russia and China.

The results depict that when firms are pursuing environmental innovation they face the challenge of not being able to keep up with the ESG readiness as it has diminishing returns (Dicuonzo et al. 2022) and it requires support from other departments too (Yadav et al. 2024). To make firms resilient against climate change they need to be ESG ready. Based on the estimation results, environmental innovations are not sufficient to make firms ESG ready for longer terms considering that these innovations are good for business competitiveness. Figure 10 plots the quadratic effect of EPAT on ESG across different AI citation moderating levels. This plot illustrates that until around 12 of EPAT there is a positive effect of EPAT on ESG but beyond that EPAT tends to reduce ESG. The major reason for the negative effect would be that further research requires incremental costs which reduces the funds available for other administrative units (Jenkins 2022). Second, while firms beyond EPAT threshold are slowing down in innovation there is an increased need for climate change innovation in response to the increasing severity of climate change (Zheng and Feng 2024). The results can enable the financial management of the firms to optimize their green innovation investment portfolio to shield them against excessive climate change along with financial risks. But the solution is provided by the study in the form of regenerative AI. It can help in making environmental patents more effective such that with the increase in generative AI, firms can achieve higher levels of ESG readiness from existing levels of environmental patents.

5 | Conclusion and Policy Implications

The research on linking generative AI and ESG readiness of businesses in BRICS countries is the need of the hour. This study explores how generative AI adoption at national level can improve the businesses' efforts to become climate change resilient. Literature has pointed out several advantages of AI adoption that lead to a competitive advantage. The findings of the study propose that generative AI research citations, along with environmental patents, can drive ESG readiness in businesses. The inverted U-shaped effect of EPAT on ESG-readiness and the positive moderating effect of generative AI show that the gains from AI research can break the diminishing returns of EPAT. This study also points towards the gains from digital infrastructure and capital investments which can help in increasing climate change preparedness.

Practically, this study helps in exploring the integration of generative AI in business strategies with a special focus on climate change mitigation. As a business adopts AI, it places itself in an optimized resource management position and is more equipped to achieve sustainable development goals. Environmental patents have shown marked improvement in performance with the supportive role of AI citations highlighting the importance of bridging technology with ESG readiness.

Policymakers must support generative AI research and development by providing funding and grants in the domain of climate change. This strategically targeted investment can accelerate business resilience. Generative AI can optimize investment in terms of data monitoring and resource use. Governments should foster AI partnerships between academia and firms to develop environmental patents. This collaborative link can help to achieve sustainable solutions. Holistic ESG readiness also requires the expansion of digital infrastructure that can help increase access to knowledge. Governments can subsidize firm investments in the domain of climate change to improve climate change resilience. All of the above policies can be clubbed into an AI governance framework that can help minimize potential risks and ensure sustainability.

The implication of using the machine learning method is that the model can be deployed to a dynamic dashboard as a central coordination platform for business decision makers. The estimated model can take feed from the investments in environmental patents and publications in generative AI to synthesize and suggest the future movement of ESG readiness. Managers can set their real-time target of ESG readiness and tune the dashboard to suggest how much environmental innovation and generative AI research is needed. The dashboard can help with early warning and real-time statistics for optimizing the environmental innovation effect on ESG readiness so that firms are over-investing compared to ESG readiness. Academic institutions can align their research priorities to test the potential of generative AI in a broader spectrum that can boost climate change resilience. Civil societies and environmental advocacy groups can use the metrics from dashboard to make business accountable for their ESG commitments and monitor the alignment of technological advancement with sustainability goals. Generative AI models can be useful in forming multi-stakeholder integration to make sustainable ecosystems. The outcomes guide the way to finetune the generative AI models for climate change mitigation. These specialized/agent-based AI models can be trained on industry specific data to provide precise and contextualized recommendations.

There should be dedicated AI-for-Climate research funds with seed money from the government and business sectors that can target the development of generative AI applications to optimize resource use and demand forecasting. Businesses that are incubating generative AI ideas with universities can be provided with tax incentives to boost the AI-enabled environmental patents. National level AI governance frameworks must have a dedicated climate specific module for public-private AI labs for BRICS countries. Governments can subsidize SMEs to promote the use of AI-powered environmental management systems. BRICS countries can make AI-climate data sharing protocols to accelerate knowledge transfer. The use of control variables like firm investment and digitization policies also point toward important AI-environmental technology adoption challenges. Firms need to allocate investments funds for AI-integration, training of employees and developing capital infrastructure. The digital infrastructure must also be focused on as it can facilitate AI-integration.

The outcome of this study is limited to the sample selected and the specification used. Future studies can explore other forms of AI research indicators in a broader context to see other advantages of AI research.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Data will be made available on request.

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