

Does Artificial Intelligence Moderate the Effect of Carbon Risk on Firm Financial Risk in Indonesia

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Abstract

This study aims to analyze the effect of carbon risk on firm financial risk and examine the moderating role of Artificial Intelligence Innovation. The research focuses on carbon-intensive companies listed on the Indonesia Stock Exchange (IDX) using a quantitative research approach. Secondary data drawn from financial statements, annual reports, and sustainability reports over the period 2018-2024 (382 observations). The data were analyzed using panel data regression and Moderation Regression Analysis (MRA). The research findings indicate that carbon risk has a positive and significant effect on firm financial risk driven by higher compliance costs, regulatory pressure, and reputational risks faced by companies with high carbon emissions. Additionally, AI innovations weakens this link by improving efficiency, risk analysis, and decision-making. The implications of this study indicate that firms should make greater use of Artificial Intelligence in their risk management strategies to strengthen financial resilience and promote sustainability. The novelty of this study lies in its analysis of the moderating effect of Artificial Intelligence on the relationship between carbon risk and firm financial risk, particularly in developing countries such as Indonesia.

Keywords: *Artificial Intelligence, Carbon Risk, Firm Financial Risk, Zmijewski X-Score.*



A. INTRODUCTION

Climate change has become a major concern in the global economy because its impacts extend beyond environmental issues and are increasingly affecting firm financial health (IPCC, 2023). Rising carbon emissions are causing companies, particularly those operating in carbon-intensive industries, to face greater regulatory pressure, higher compliance costs, reputational challenges, and transition uncertainty (Wang et al., 2022). Consequently, carbon risk is receiving increasing attention in corporate finance, as it encompasses the potential financial consequences arising from environmental regulations, carbon-related costs, and the transition toward a low-carbon economy (Wang, 2023). Previous research indicates that high carbon risk is driven by declining profitability, deteriorating financial performance, and the significant financial burden borne by companies (Duan et al., 2025; Zhang et al., 2025). Furthermore, investors and creditors also perceive companies with high pollution levels as being more vulnerable to high transition and reputational risks, which can affect the company financing condition and market value (Lee & Cho, 2021; Palea & Drogo, 2020). New findings suggest that firms facing higher carbon risk are more exposed to climate-related uncertainty, encouraging them to hold larger cash reserves as a protective measure (Thi et al., 2025).

Although research on this issue is expanding, empirical evidence regarding the relationship between carbon risk and firm financial risk remains limited. Some studies suggest that increased carbon emissions and ESG practices can reduce the risk of firm financial distress (Miah et al., 2021; Ding et al., 2023). Furthermore, Khatib et al. (2023) also state that investors tend to view rising emissions as an unfavorable signal, which can lead to losses in firm profitability and market valuation. Meanwhile, other researchers have revealed that increased carbon and ESG disclosure is important for firm in reducing risk and building trust in the market (Lu et al. 2021; Singhania & Gupta 2024). These mixed findings suggest that the relationship between carbon risk and firm financial risk remains unresolved, necessitating further empirical investigation.

At the same time, technological innovation plays a crucial role in helping firm address carbon-related challenges. Artificial Intelligence (AI) innovation is one of the most significant advancements that can help firm process large amounts of data, identify patterns, and make better and more informed decisions (Fritz-Morgenthal et al., 2022). AI can also be linked to the ability to make more accurate estimates of carbon emissions, real-time monitoring, more efficient production, and greater management efficiency (Hua et al., 2025; Wang et al., 2024). Furthermore, the adoption of AI is associated with increased productivity, efficient resource utilization, and lower carbon emissions (Li et al., 2025; Yu et al., 2025). From a financial perspective, AI enhances predictive analytics and helps companies better identify and manage risks (Vyas, 2025). Overall, these findings indicate that AI plays a crucial role in helping companies address carbon-related challenges while mitigating the financial pressures arising from environmental issues.

Nevertheless, the role of AI in this relationship remains inconsistent. Zhao et al. (2021) note that the relationship between financial risk, technological progress, and emissions remains dynamic. Consequently, carbon-related risks exhibit complex characteristics and require further analytical approaches (Siddique & Karim (2025). Dhar (2020) also points out that AI consumes more energy, thereby contributing to increased carbon emissions. According to the current literature, several research gaps remain. First, previous research has yet to provide consistent evidence regarding the relationship between carbon risk and firm financial risk. Second, although AI is a strategic and important tool for companies, its use as a moderating variable has not been sufficiently explored in financial studies. Third, previous research has primarily focused on developed countries, so evidence from developing countries such as Indonesia remains limited (Vu et al., 2025). This gap is significant because differences in technological readiness, institutional structures, and levels of carbon exposure influence the relationship across various countries. Therefore, this study aims to examine the impact of carbon risk on firm financial risk and to analyze the moderating role of Artificial Intelligence innovation in carbon-intensive companies listed on the Indonesia Stock Exchange.

B. LITERATURE REVIEW

This study based on Stakeholder Theory. According to (Freeman, 1984), an organization must respond to the interests of all stakeholders, including shareholders, creditors, regulators, customers, employees, and the general public those affected by its activities. From this perspective, business sustainability depends on the ability to maintain the trust, legitimacy, and support of stakeholders. Corporate governance must demonstrate how stakeholders can participate in and influence management decisions, including how the company addresses environmental and financial issues (Agustin et al., 2025). When a company fails to meet stakeholder expectations, it risks losing legitimacy, facing a decline in public trust, and facing greater financial pressure.

When it comes to environmental issues, stakeholder expectations are becoming increasingly important because, in addition to profitability, companies are also evaluated based on how they manage sustainability and climate risks. Pressure from stakeholders is driving companies to actively address environmental issues, rather than merely complying with regulations (Huang & Xiao, 2023). Sastroredjo & Suganda (2025) also explain that weak governance or unethical behavior can erode public trust and lead to financial risks. Previous research has also demonstrated that environmental responsibility can yield economic benefits. Kalash (2021) shows that strong environmental performance can lead to improvements in capital structure and profitability. Additionally, Aydoğmuş et al. (2022) note that ESG practices have the potential to enhance firm value and reduce financial risk. Meanwhile, Widyantoro & Rusmanto (2025) show that pressure from stakeholders, green dynamic capabilities, and green innovation all have a positive impact on financial performance. Therefore, Stakeholder Theory provides an important foundation for explaining how carbon risk can affect firm financial risk.

In addition, Legitimacy Theory also supports this study. This theory explains how companies strive to ensure their operations remain relevant and aligned with societal values, norms, and expectations. According to this perspective, company sustainability depends on social support and economic performance. Khan (2025) divides legitimacy theory into two perspectives; substantive legitimacy and symbolic legitimacy. Symbolic legitimacy occurs when a company merely implement meaningful changes. Meanwhile, substantive legitimacy occurs when a company takes concrete actions that genuinely yield results for both the environment and the company financial condition.

Carbon risk refers to the potential financial impacts arising from carbon emissions, environmental regulations, transition costs, and market reactions to environmental impacts. Companies with high carbon exposure typically face higher compliance costs, more challenging financing conditions, and greater uncertainty, which can undermine their financial stability (Wang et al., 2022; Wang, 2023). Previous research emphasizes that higher carbon emissions are associated with lower firm performance and market value, implying that environmental risk exposure can exert economic pressure on firms (Lee & Cho, 2021; Houque et al., 2022). Miah et al. (2021) also found that higher carbon emissions can reduce a firm financial and market

performance. Meanwhile, Dewaelheyns et al. (2023), demonstrate that carbon risk tends to have a negative effect on firm value, particularly for firms highly exposed to carbon risk due to the uncertainty of carbon policies. Conversely, better carbon performance is associated with lower firm risk (Al-Fakir Al Rabab'a et al., 2024). Therefore, higher carbon risk is expected to increase firm financial risk.

H₁: Carbon Risk has a significant positive effect on Firm Financial Risk.

Innovations in Artificial Intelligence (AI) are expected to mitigate the impact of carbon risks on corporate financial risks. Companies with high carbon exposure generally face stricter regulatory scrutiny, higher transition costs, and greater financial uncertainty. In this context, AI helps companies process large volumes of data, assess risks more effectively, and support faster and more accurate decision-making (Fritz-Morgenthal et al., 2022; Vyas, 2025). Several studies also indicate that AI enables companies to address carbon-related challenges more efficiently. AI can help reduce carbon emission intensity and drive innovation in green technologies (Chen et al. 2022). Additionally, AI allows companies to monitor emissions in real-time and generate more precise forecasts (Hua et al., 2025). The productivity gains resulting from AI adoption can also contribute to reduced emissions levels within companies (Wu & Zhou 2025). Overall, this suggests that AI improves environmental performance while strengthening corporate governance by enhancing information transparency and supporting access to financing (Xie et al., 2025). These findings suggest that companies with stronger AI innovations tend to manage carbon-related exposures more effectively and mitigate their financial consequences. Therefore, AI innovations are expected to mitigate the positive impact of carbon risk on firm financial risk.

H₂: Artificial Intelligence innovation weakens the positive effect of Carbon Risk on Firm Financial Risk.

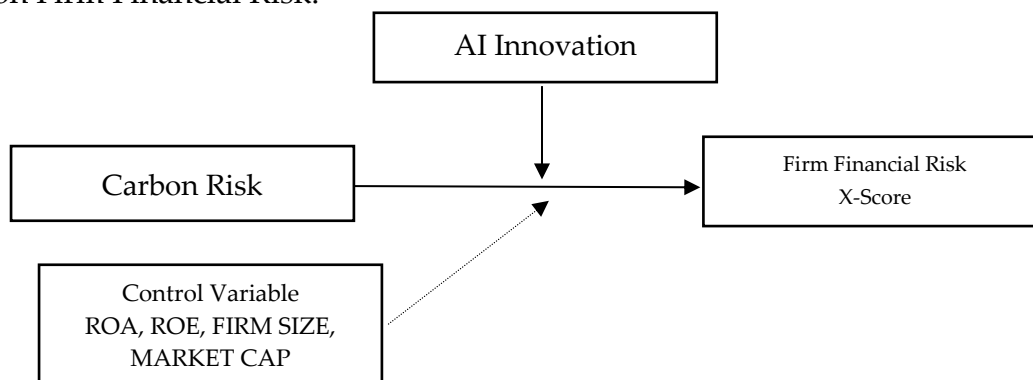


Figure 1. Conceptual Framework

C. METHOD

This study employs a quantitative method with an exploratory research design to examine the impact of carbon risk on firm financial risk and to assess the moderating role of Artificial Intelligence (AI) innovation. The study utilizes secondary data, primarily financial information extracted from annual reports and sustainability reports available on the official website of the Indonesia Stock Exchange (IDX) and the

companies' official websites. In this study, carbon emissions data is used as a proxy for carbon risk, while information related to the use of Artificial Intelligence is used to represent AI innovation. The population consists of carbon-intensive companies listed on the IDX, and the sample was selected using purposive sampling to ensure that the data is available and relevant to the research objectives (Tajik et al., 2024).

Table 1. Sampling Criteria

Criteria	Total
Total Firms listed on IDX	943
Number of firms with carbon risk data	76
Number of firms with carbon risk data in 2018	42
Number of firms with carbon risk data in 2019	43
Number of firms with carbon risk data in 2020	47
Number of firms with carbon risk data in 2021	59
Number of firms with carbon risk data in 2022	67
Number of firms with carbon risk data in 2023	73
Number of firms with carbon risk data in 2024	76
Total firm-year observation	407

Source: Secondary Data Processed, 2026.

Firm financial risk reflects the likelihood of its financial condition deteriorating and, if not properly managed, can lead to a financial crisis (Zhang, 2022). As the dependent variable, firm financial risk was measured using the Zmijewski X-Score model, which is used to predict the likelihood of a firm financial distress (Heniwati et al., 2025). This model is considered appropriate because it captures the firm's financial condition through three key dimensions, namely profitability, leverage, and liquidity. In addition, Luu et al. (2026) used the Zmijewski model as an alternative proxy for bankruptcy risk and firm financial health, indicating that the model remains relevant in more recent empirical studies. Gulo et al. (2025) further explain that the Zmijewski model evaluates financial distress using these three core financial ratios, making it relatively simple and effective for identifying financial vulnerability. The X-Score value has a positive relationship with financial distress. This means that the higher the X-Score value, the greater the probability that the firm will face financial difficulties or bankruptcy (Azam et al., 2023). In addition, Kozak & Wierzbowska (2025) explain that companies with an X-Score below zero are generally classified as being in sound financial condition, while a score above zero indicates potential financial problems. Thus, the Zmijewski model is suitable for this study because it directly reflects the level of firm financial risk. The X-Score formula used in this study is as follows:

$$XSCORE = -4.3 - 4.5A + 5.7B - 0.004C$$

Source: (Martanti et al., 2021)

Where: A = Return on Assets (ROA), B = Leverage (Debt Ratio), C = Liquidity (Current Ratio) This model is constructed from three financial components, namely profitability, leverage, and liquidity. Return on Assets reflects the firm's ability to generate earnings from its total assets, leverage indicates the extent to which the firm

depends on debt financing, and liquidity captures the firm's ability to meet its short-term obligations (Jihadi et al., 2021). The resulting X-Score is then used to indicate the level of firm financial risk, where a higher score reflects a greater likelihood of financial distress.

In this study, carbon risk serves as an independent variable and measured by the total carbon dioxide (CO₂) emissions generated by the company in tons of CO₂e. Previous studies generally use this measure as a direct proxy for carbon risk because higher emission levels reflect greater exposure to carbon-related pressures, such as environmental regulations, transition risks, and market expectations (Wang, 2023). Total carbon emissions are considered relevant because companies with higher emissions are generally more vulnerable to carbon-related costs and external scrutiny, which could potentially affect their financial health. Before being included in the regression model, the carbon emissions variable was transformed into a logarithmic form. This transformation is intended to reduce scale differences between companies and improve data distribution, as emission levels can vary substantially across companies. Therefore, this study uses logCarbon as a proxy for carbon risk.

Furthermore, Artificial Intelligence (AI) innovation serves as a moderating variable. This indicates the extent to which companies have developed and integrated AI-related capabilities into their operations and decision-making. In this study, AI innovation is measured by the number of AI-focused patents held by each company. Patents are used because they demonstrate a company's commitment to innovation and provide tangible evidence of technological capability. A higher number of AI patents reflects a higher level of AI innovation within the company. The use of patents as a proxy is consistent with the view that innovation should be assessed not only through technology adoption but also through tangible evidence of technological progress. In this study, companies with stronger AI innovation are expected to have better analytical capabilities, more effective monitoring systems, and more flexible decision-making, which can help mitigate the financial impact of carbon-related risks. Similar to carbon risk, this variable is transformed into a logarithmic format in the regression model and as logAIINOV for Artificial Intelligence Innovation.

This study includes four control variables, namely Return on Assets (ROA), Return on Equity (ROE), Firm Size, and Market Capitalization. These variables are included to reduce omitted-variable bias and to ensure that the relationship between carbon risk and firm financial risk is not explained solely by basic firm characteristics. ROA is measured as net income divided by total assets, while ROE is measured as net income divided by total equity (Hong & Id, 2023). Both variables are included because profitability is closely related to firms' financial resilience. Firms with stronger profitability are generally more capable of absorbing environmental pressure and maintaining financial stability. Firm Size is measured using the natural logarithm of total assets (Suprpto, 2023). Larger companies typically have stronger financial resources, more diversified business activities, and better access to external financing, all of which can influence their level of financial risk. Market capitalization is measured using the natural logarithm of market capitalization (Nguyen, 2026). This

variable is included because market value can reflect how investors view the firm and also indicates the firm's overall strength, both of which may be related to financial vulnerability.

To test the hypotheses, this study uses two regression models. The first model is used to test the direct effect of carbon risk on a firm financial risk. The second model is used to test whether AI innovation moderates the relationship between carbon risk and a firm's financial risk. The regression models are written as follows:

Model 1: Basic Regression (without moderation)

$$FR_{it} = \alpha + \beta_1 \log CR_{it} + \beta_2 ROA_{it} + \beta_3 ROE_{it} + \beta_4 FS_{it} + \beta_5 \log MC_{it} + \varepsilon_{it}$$

Model 2: Regression with Artificial Intelligence Innovation Moderation

$$FR_{it} = \alpha + \beta_1 \log CR_{it} + \beta_2 ROA_{it} + \beta_3 (\log CR_{it} \times \log AI_{it}) + \beta_4 ROA_{it} + \beta_5 ROE_{it} + \beta_6 FS_{it} + \beta_7 \log MC_{it} + \varepsilon_{it}$$

Where: FR_{it} = Firm Financial Risk, $\log CR_{it}$ = Carbon Risk, $\log AI_{it}$ = Artificial Intelligence Innovation, $(\log CR_{it} \times \log AI_{it})$ = interaction variable, ROA_{it} = Return on Assets, ROE_{it} = Return on Equity, FS_{it} = Firm Size, $\log MC_{it}$ = Market Capitalization, α = constant, β = regression coefficient, ε = error term, i = firm, t = year. Model (1) is designed to test the direct effect of carbon risk on firm financial risk. Model (2) extends the analysis by incorporating AI innovation and the interaction term between carbon risk and AI innovation. A significant interaction coefficient indicates that the effect of carbon risk on firm financial risk depends on the level of AI innovation.

Table 2. Variable Measurement

Variable	Measurement	Indicator	Source
Firm Financial Risk	Using the Zmijewski X-Score	X-Score = $-4.3 - 4.5ROA + 5.7Leverage - 0.004Liquidity$	(Martanti et al., 2021)
Carbon Risk	Total carbon emissions (CO ₂)	Ton CO ₂ e	(Q. Wang, 2023)
Artificial Intelligence Innovation	Number of AI-related patents held by the company	Number of AI patents	Vyas (2025)
Return On Assets (ROA)	Net income divided by total assets	Net Income/Total Assets	(Hong & Id, 2023)
Return On Equity (ROE)	Net income divided by total equity	Net Income/Total Equity	(Hong & Id, 2023)
Firm Size	Natural logarithm of total assets	Ln(Total Assets)	(Suprpto, 2023)
Market Capitalization	Natural logarithm of market capitalization	Ln(Market Cap)	(Nguyen, 2026)

D. RESULT AND DISCUSSION

The descriptive statistical analysis was conducted to provide an overview of the characteristics and distribution of the research data. This analysis includes key statistical measures, such as the mean, standard deviation, minimum, and maximum values, to identify the general patterns and variations in the data. The results of the descriptive statistical analysis are presented in Table 3.

Table 3. Descriptive Statistical Results

	N	Mean	Median	Minimum	Maximum
CARBON RISK	407	7279.925	557.687	15.421	254276.372
AI INNOVATION	407	39.135	12.000	1.000	598.000
ROA	407	0.979	0.056	-7.008	77.055
ROE	407	9.137	0.145	-254.396	345.546
FIRMSIZE	407	31.623	31.439	28.378	35.426
MARKETCAP	407	87.100	31.430	0.002	1193.000
X-SCORE	407	-6.355	-2.992	-349.315	30.092

Note: Market capitalization is reported in trillion rupiah to improve table readability.

Table 2 presents descriptive statistics for all variables used in this study and provides a summary of the sample data. The results of the analysis show that carbon risk has a mean value of 7,279.925, with a minimum value 15.421 and a maximum value 254,276.372, indicating considerable variation in carbon emissions among companies. Meanwhile, the firm financial risk variable, measured using the Zmijewski XScore, has a mean of -6.355, with a range -349.315 and 30.092, indicating considerable variation in the financial condition of the companies. The moderation variable, Artificial Intelligence innovation, has a value 39.135, indicating that AI innovation in these companies remains limited. ROA has a mean of 0.979 and ROE has a mean of 9.137, showing that profitability varies across firms, with some companies generating stronger returns than others. Firm Size shows relatively low variation, while Market Capitalization varies more widely across the sample.

Table 4. Pearson Correlation Test

	X-SCORE	CARBON RISK	AI INNOVATION	ROA	ROE	FIRM SIZE	MARKETCAP
X-SCORE	1.000						
CARBON RISK	-0.008 (0.873)	1.000					
AI INNOVATION	-0.021 (0.673)	0.001 (0.980)	1.000				
ROA	-0.992*** (0.000)	0.034 (0.497)	0.008 (0.877)	1.000			
ROE	-0.361*** (0.000)	0.169*** (0.001)	-0.018 (0.713)	0.360*** (0.000)	1.000		
FIRMSIZE	0.131*** (0.008)	-0.003 (0.956)	-0.194*** (0.000)	-0.141*** (0.004)	0.060 (0.226)	1.000	
MARKETCAP	0.038 (0.442)	-0.012 (0.807)	-0.105** (0.034)	-0.062 (0.213)	0.036 (0.471)	0.605*** (0.000)	1.000

The results of correlation show that Carbon Risk does not have a significant relationship with X-Score, which is indicated by the coefficient -0,008 and the value $p = 0,873$, suggesting that it does not directly impact financial risks in companies.

Similarly, Artificial Intelligence Innovation does not demonstrate a significant relationship with X-Score, which is illustrated by the coefficient -0,021 and p-value = 0,673. On the other hand, variables for profitability exhibit more substantial correlations with financial risks. Both ROA and ROE negatively correlate with X-Score, which indicates that companies with higher profitability face lower financial risks. Besides, Artificial Intelligence Innovation negatively correlates with Firm Size and Market Capitalization, indicating that innovations related to artificial intelligence occur more frequently in smaller companies. Overall, since all coefficients of correlation are below 0,8, there are no signs of multicollinearity in the model, and therefore, it can be used for regression analysis.

Table 5. Regression and Moderation Test

	X-SCORE (1)	X-SCORE (2)
logCARBON	0.352* (1.95)	0.397** (2.11)
logAIINOV		0.249 (1.55)
CARAI2		-0.001*** (-3.07)
ROA	-4.509*** (296.95)	-4.508*** (-322.95)
ROE	-0.002 (-0.91)	-0.002 (-0.99)
FIRMSIZE	-0.085 (-0.34)	-0.162 (-0.62)
logMARKETCAP	-0.639*** (-5.32)	-0.360*** (-5.03)
_cons	9.459* (1.67)	11.063* (1.91)
Year Fe	Yes	Yes
r2	0.986	0.986
r2_a	0.985	0.985
N	407	407

t statistics in parentheses* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The results of the regression analysis reveal that the risk of carbon emissions (logCarbon) has a positive and statistically significant impact on the financial risk of the companies. In Model (1), the coefficient increases to 0.352 with the significance level of $p < 0.1$, while in Model (2), the coefficient increases to 0.397 with the significance level of < 0.05 . This means that firms exposed to a higher risk of carbon tend to have greater financial risks. Model (2) indicates that AI Innovation (logAIINOV) does not have a significant impact on a firm financial risk. However, the interaction between Carbon Risk and AI Innovation has a coefficient of -0.001 and is significant at $p < 0.01$. In other words, these results suggest that Artificial Intelligence Innovation acts as a moderator of the relationship between carbon risk and a firm financial risk.

Table 6. Robustness Test Based on Firm Size

	(1) XSCORE	(2) XSCORE	(3) XSCORE	(4) XSCORE
logCARBON	0.577** (2.01)	0.652** (2.16)	0.063 (0.90)	0.078 (1.07)
ROA	-4.526*** (-185.07)	-4.524*** (-204.75)	-674*** (-50.09)	-4.684*** (-50.77)
ROE	0.004 (0.88)	0.004 (0.88)	-0.001 (-0.83)	-0.001 (0.94)
FIRMSIZE	-0.842 (-1.28)	-0.868 (-1.38)	0.028 (0.17)	-0.033 (-0.21)
logMARKETCAP	-0.173 (-0.95)	-0.177 (-0.98)	-0.421*** (-5.92)	-0.411*** (-5.55)
logAIINOV		0.303 (1.35)		0.179 (1.26)
CARAI2		-0.002*** (-2.73)		-0.001** (-2.31)
_cons	24.762* (1.69)	24.964* (1.82)	10.246** (2.04)	11.608** (2.36)
Year FE	Yes	Yes	Yes	Yes
r2	0.990	0.990	0.679	0.681
r2_a	0.989	0.989	0.658	0.656
N	226	226	181	181

t statistics in parentheses* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Additionally, a robustness test was conducted using firm size subsample analysis, divided into low firm size and high firm size. Based on the results in Table 6, show that Carbon Risk have a positive on Firm Financial Risk. Also, the interaction between Carbon Risk and Artificial Intelligence Innovation negative and significant, consistent with the regression results in Table 5.

The findings of this study indicate that carbon risk has a positive and significant effect on firm financial risk. The finding is consistent with Bolton & Kacperczyk (2021), who argue that firms exposed to higher levels of carbon risks face greater financial consequences, including increased investor pressure and greater transition risks when making the transition to low carbon economy. Palea & Drogo (2020) found that higher levels of carbon emissions were linked to higher costs of debt financing, meaning that lenders require premium risk. Likewise, Kleimeier & Viehs (2021) show that firms with higher levels of emissions usually have higher borrowing costs. These findings are further supported by Angie et al. (2025) where it has been found that carbon management practices are related to organizational performance. It indicates that carbon-related issues cannot be seen merely as environmental concerns but also as factors that can affect financial conditions within companies. Further, Trinks et al. (2020) have also observed that organizations that efficiently manage carbon emissions tend to perform better financially and have lower systematic risks. In general, it indicates that factors related to carbon are closely associated with financial risks within firms. Thus, H1, which states that Carbon Risk significantly positively impacts Firm Financial Risk, is supported.

Furthermore, this study finds that Artificial Intelligence Innovation does not have a direct effect on firm financial risk, but it significantly moderates the relationship between carbon risk and financial risk. This implies that companies with more advanced AI Innovation are better prepared to manage the financial consequences of carbon risk. In this regard, the findings of this study are also consistent with those of Li et al. (2025), who found that companies with stronger AI Innovation are able to mitigate the adverse consequences of carbon risk. Furthermore, AI can assist companies in enhancing productivity, identifying potential risks early on, and improving the accuracy of data-driven decision-making (Peng et al., 2025). Therefore, H2, which states that Artificial Intelligence Innovation moderates the relationship between carbon risk and firm financial risk, is supported.

E. CONCLUSION

From this study, it is evident that carbon risk positively impacts firm financial risk, meaning that companies with more carbon risk experience financial risks. Also, the study reveals that the role played by Artificial Intelligence Innovation is to mitigate the relationship between carbon risk and firm financial risk. This implies that companies with more AI Innovation are capable of mitigating the effects of carbon risk on their financial performance. From the study, it is evident that carbon risk is not only a financial. Theoretically, this study supports Stakeholder Theory and Legitimacy Theory by demonstrating that environmental exposure influences the emergence of pressure from stakeholders and the public, which can pose financial risks to companies. However, the findings also suggest that technology specifically, Artificial Intelligence innovation can help companies respond to such pressure more efficiently. In conclusion, this study provides additional evidence suggesting that environmental risks and technological innovations play equally significant roles in explaining firm financial risks. This indicates that companies need to strengthen their carbon risk management and invest more in AI technologies capable of enhancing their analytical approach to risk. From a practical perspective, these findings suggest that carbon risk management and investment in AI innovation need to be enhanced to improve monitoring, risk analysis, and decision-making. The findings are also useful for investors, creditors, and regulators since the results show that exposure to carbon emissions and technological readiness have equal relevance in assessing company resilience and financial stability. This study has several limitations. This study is only conducted on carbon-intensive companies that are listed on the Indonesia Stock Exchange, observing a relatively limited period, and measures the carbon risk and AI innovation using total carbon emission and AI-related patent numbers respectively. Therefore, future research is recommended to employ a larger sample size, observe a larger period of time, and measure carbon risk and AI innovation using different proxies. Future research can also incorporate other factors that can further elaborate on firm financial risk.

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