

ESG and Financial Risk: Does AI Innovation Strengthen the Relationship?

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ABSTRACT

This study aims to examine the impact of Environmental, Social, and Governance (ESG) performance on a firm's financial risk and to explore the moderating role of Artificial intelligence (AI) innovation. This research uses a quantitative approach with secondary data from Indonesia companies listed on Indonesia Stock Exchange for the period 2018 – 2024, resulting in 340 observations. The firm financial risk is measured using Altman Z-Score and Zmijewski X-Score, while the analysis is conducted using panel regression with fixed effects. The results show that ESG performance does not have a significant effect on financial stability as measured by Z-Score, suggesting that the financial benefits of implementing ESG might not be immediately visible in the short-term. However, ESG significantly reduces financial distress risk as measured by the X-Score, indicating that stronger ESG practices increase financial resilience. AI innovation contributes to improving financial outcomes, but does not consistently strengthen them. Overall, this study concludes that ESG performance supported by AI innovation has the potential to lower financial distress. This study contributes to the growing sustainability finance literature by providing empirical evidence from an emerging market on how ESG performance and AI innovation jointly influence firm financial risk.

Keywords: AI Innovation; ESG Performance; Firm Financial Risk; X-Score; Z-Score

INTRODUCTION

In the past few years, Environmental, Social, Governance (ESG) has undergone changes from merely a voluntary practice to one of the strategic factors in corporate management and investment decisions due to increasing awareness of sustainability (Bai & Kim, 2024). In Indonesia, this is reinforced by OJK Regulation Number 51/POJK.03/2017 stating that financial institutions, issuers, and public companies must create and report their sustainability including ESG aspects (OJK, 2017). This indicates that ESG has an important role in supporting business sustainability and corporate competitiveness. The implementation of sustainability provides strategic benefits, including improving operational efficiency, reputation, investor trust, access to funding, and company valuation (Wu et al., 2022). The Company is no longer only profit-oriented, but also on sustainability as part of its long-term strategy (Agustin et al., 2024). As companies increasingly integrate sustainability into their long-term business strategy can have a positive impact on the company's value and sustainability. Overall, ESG also contributes to stronger stakeholder confidence and greater financial stability (Zheng et al., 2025). Therefore, companies with higher ESG performance tend to demonstrate more stable and sustainable financial performance.

In addition, ESG also plays an important role in reducing firm financial risk. Good environmental practices help companies minimize legal risks, such as fines and sanctions, by ensuring compliance with environmental regulations (Zheng et al., 2025). Strong social policies also reduce reputational risks, as companies that prioritize employee welfare, community relations, and business ethics tend to gain greater stakeholder trust (Li et al., 2021). Good governance enhances transparency and disclosure quality, reducing information asymmetry between

management and investors. The combination of these three aspects makes ESG an effective risk management instrument, where companies with high ESG Performance generally face lower financial distress. Globally, ESG development is driven by international commitments such as the Paris Agreement and the rapid growth of ESG-based investment, making sustainability a global business standard (Naysary et al., 2025; Chau et al., 2025). In addition, sustainability reporting has become a common practice among major companies as a form of transparency and accountability to stakeholders, which shows that ESG is no longer an option but a global standard. However, ESG implementation still faces challenges, a report by KPMG International Limited found that among 750 companies that have been researched, only a small proportion had adequate ESG awareness, policies, and systems, while around 58% were still not fully prepared for ESG assessments (Wilowski, 2023).

Besides offering benefits in operational and reputation aspects, ESG implementation is increasingly linked to a company's ability to maintain financial stability reflects its ability to keep healthy financial conditions, meet obligations, and reduce the risk of financial distress amid economic uncertainty (Yun et al., 2024). Companies with better stability tend to have higher resilience against external pressures and stronger business continuity. Cardillo and Torluccio (2023) research shows that ESG activities help improve a company's financial stability, backed up by Habib (2023) who found that companies with higher ESG performance tend to have lower risk of bankruptcy. However, previous research still shows inconsistent findings, where ESG implementation doesn't always have a direct impact on short-term financial stability because it requires quite a large initial investment as well as an operational adjustment process before economic benefits can be realized (Rojo-suárez & Alonso-conde, 2023; Xu et al., 2022).

Along with the increasing complexity of ESG reporting, AI has become an important tool for processing ESG data and supporting risk management. However, AI implementation remains limited due to high initial investment costs, including infrastructure, model development, system maintenance, and employee training (Boonmee et al., 2025). Companies also need to bear the cost of system maintenance and continuous data management so that AI can function optimally (Gelashvili-Luik et al., 2025). In addition, the limited availability of employees with AI expertise continues to hinder the optimization of AI utilization in companies (Brey & van der Marel, 2024).

Previous studies between relationship ESG performance and firm financial risk show mixed results. Several studies have found that ESG performance reduces bankruptcy risk and improves financial stability (Gao et al. 2025). While others report insignificant short-term effect due to high investment cost and the long-term nature of ESG benefits (Handoyo, 2026). Differences in financial distress measurements, such as the Z-Score and X-Score, also contribute to inconsistent findings. Therefore, this study expands previous research by introducing AI innovation as a moderating variable, since AI technology can improve data analysis, reporting transparency, risk detection and decision-making quality in ESG implementation (Liu et al., 2026). Although prior studies have discussed ESG and digital transformation separately, research on the moderation of AI innovation in the relationship between ESG performance and firm financial risk is still limited (Chen & Wang, 2024).

This study also provides practical implications by showing that effective ESG implementation supported by AI innovation can reduce financial risks and increase stakeholder trust. Companies integrating sustainability practices with AI innovation tend to have better financial stability and long-term sustainability prospects, making ESG performance and AI innovation important considerations in evaluating corporate value and risk management capabilities (Friede et al., 2015).

LITERATURE REVIEW

Stakeholder Theory

Freeman and David (1983) stakeholder theory argues that the development and growth of a company is closely related to the role of stakeholders. Therefore, companies need to consider the interests of these parties in every decision-making process and policy implementation. In corporate governance, stakeholders include various parties such as managers, consumers, investors, and other parties related to the company's activities. According to Awa et al. (2024) a company's success doesn't just focus on the interests of shareholders, but also on how the company can pay attention

to the interests of every stakeholder including employees, customers, society, and others. This theory emphasizes that good management of relationships with stakeholders can create value and improve company performance.

Currently, governments and companies are increasing awareness of the importance of stakeholder theory in assessing organizational performance. In the context of ESG, this theory serves as a theoretical basis that connects various factors that can affect company performance and makes an important contribution to the development of academic studies (Agustin et al., 2025). In addition, this theory suggests that ESG represents a company's response to stakeholder demands through fair and transparent environmental, social, and governance practices (Wai-Khuen et al. 2023). Based on stakeholder theory, companies with strong ESG practices tend to reduce uncertainty and firm financial risk by increasing stakeholder trust, strengthening reputation, and creating more stable relationships with investors, employees, and society (Liu, 2025).

Resource Based View Theory

Wernerfelt (1995) through Resource-Based View (RBV) theory, a company can gain a competitive advantage if it possesses resources and capabilities that are valuable, rare, difficult to imitate, and not easily replaceable. Novitarini & Sudana (2024) explains that a company's internal resources are the main foundation in creating performance and long-term sustainability. In this study, ESG performance can be seen as a strategic intangible resource because the implementation of good environmental, social, and governance practices can enhance reputation, legitimacy, transparency, and stakeholder trust (Jiang & Lin, 2026). These capabilities help companies reduce business uncertainty and suppress firm financial risk through improved operational stability and corporate governance quality. Research by Yun et al. (2024) also shows that companies with strong ESG tend to have better financial stability and lower bankruptcy risk because they are able to manage risks more effectively and increase investor confidence.

From an RBV perspective, AI innovation can be seen as one of the strategic capabilities that supports ESG-based resource management. AI enables companies to analyze ESG data more quickly and accurately, helping identify potential financial distress risks and improve decision-making quality (Shafique et al. 2026). In this study, AI innovation acts as a technological capability that strengthens the effectiveness of ESG implementation in reducing firm financial risk. The integration of ESG and AI can create sustainability competitive advantage and improve operational efficiency, risk management, and financial stability (Cheng & Yang, 2026). Research based on the RBV shows that AI innovation can become a strategic capability of a company that enhances operational efficiency and risk management, thereby strengthening ESG performance and supporting the company's financial stability (Jackson et al., 2024).

Relationship Between ESG Performance and Firm Financial Risk

ESG performance shows a firm performance in the environmental, social, and governance aspects and also demonstrates its ability to meet sustainability responsibilities (Feng et al., 2025). Corporations with strong ESG generally reflect stronger governance practices and greater transparency, so that it can help reduce the firm risk (Agustín et al., 2025). Several studies show that ESG performance has a negative significant effect on a firm's financial risk, indicating that better ESG performance leads to lower financial risk. These findings are supported by Zheng et al. (2025) which explains that ESG performance can improve financial stability while reducing the level of risk. This finding is supported by research conducted by Hoepner et al. (2024), Khan (2019) found that ESG practices and involvement can act as a mechanism in corporate risk management, because ESG indicators can be a leading indicator for company stability and performance. Therefore, companies with high ESG practices will have a stable financial condition and low risk level. This explanation aligns with stakeholder theory, whereby the importance of maintaining transparency and positive stakeholder relationships to reduce financial risk (Katsamposxakis et al., 2026).

Several studies also explain that ESG Performance has a negative effect on firm risk, it means that a transparent company with high ESG can lower its risk level (Suttipun, 2023). In addition, effective ESG implementation can also improve company performance, meaning that

better ESG practices are related to higher firm performance (Tao, 2023). According to research by Cohen (2023) ESG performance has a significant relationship with firm risk as measured by Altman Z-Score and explained that companies with better ESG performance will also have higher financial stability, meaning the level of bankruptcy and financial risk becomes lower. These results are supported by Antunes et al. (2023), where companies with better ESG performance have more stable financial conditions and lower risk level. However, ESG research and firm financial risk measured using the Zmijewski X-Score did not always show a strong direct relationship. According to research Handayani (2025), shows that manufacturing companies with high ESG performance are in stable financial condition so that they are classified as not experiencing financial distress. These findings are also supported by recent research that shows that good ESG implementation can help companies reduce financial risks and improve stability (Gao et al., 2025; Wiwaha & Dalimunthe, 2025). Thus, it can be concluded that ESG Performance tends to contribute to lowering firm financial risk, although the direction of the relationship can vary depending on the measurement model.

The relationship between ESG performance and a firm financial risk can be explained through a combination of stakeholder theory and the RBV. According to stakeholder theory, companies that adopt ESG practices can meet stakeholders' expectations through greater transparency, governance, and social responsibility, which strengthens investor trust and reduces financial uncertainty. On the other hand, the RBV sees ESG as a strategic resource based on internal capabilities that is hard to imitate and can generate a long-term competitive advantage by improving reputation, operational efficiency, and risk mitigation. That's why the better the ESG performance, the lower the firm financial risk.

H_{1a}: ESG performance has a negative effect on firm financial risk proxied by Z-Score.

H_{1b}: ESG performance has a negative effect on firm financial risk proxied by X-Score.

The Moderating Role of AI Innovation on the impact of ESG Performance

AI Innovation refers to the use of Artificial Intelligence technology to improve products, services, and business processes more efficiently and innovatively, thereby increasing company competitiveness (Machucho & Ortiz, 2025). AI also helps companies to develop their capabilities quickly to change business environment and create transformative innovation (Gonzales, 2023). In ESG implementation, AI supports more accurate ESG data analysis, greater reporting transparency, and faster risks identification, which can strengthen risk management and support the company's financial stability (Kaleem et al., 2024; Song et al., 2025).

Several studies show that the application of AI can strengthen the positive impact of lowering firm financial risk, which means that when a company has good ESG performance, it can reduce financial risk if the company adopts AI (Song et al., 2025). Research by Chen et al. (2022) shows that the use of AI can significantly improve company performance, where the influence occurs through increased creativity and quality of decision-making in the company. The combination of ESG and AI on firm financial risk measured using Z-Score shows a negative and significant influence, which means that the combination of both is able to reduce the level of corporate financial risk. The interaction of the two shows that the implementation of ESG supported by AI Innovation can strengthen the company's ability to identify, monitor, and manage risks more effectively (Kumar et al., 2025).

Research on ESG and AI Innovation using the X-Score shows a significant relationship, indicating that ESG implementation can improve corporate governance and risk management. Several studies explain that good ESG implementation can encourage companies to increase transparency. When combined with AI, companies can conduct more complex and accurate data analysis, improve transparency, identify financial risks earlier, and enhance decision-making quality (Habibinejad et al., 2025). According to Lim (2024) higher ESG and AI implementation also strengthen a company's ability in managing financial risk, leading to lower X-Score risks levels. In addition, AI enables more accurate risk analysis and earlier detection of financial problems, thereby improving the company's financial resilience (Luo, 2025).

The role of innovation in AI as a moderator can be explained through the RBV, which sees AI as a strategic technological capability that strengthens the use of a company's resources.

Integrating AI allows companies to process ESG data more quickly and accurately, improve decision-making quality, and boost their ability to identify and manage risks. From a stakeholder theory perspective, using AI also enhances the quality of transparency and accountability in ESG, which reinforces stakeholders' trust in the company.

H_{2a}: AI innovation moderates the impact of ESG performance on firm financial risk proxied by Z-Score

H_{2b}: AI innovation moderates the impact of ESG performance on firm financial risk proxied by X-Score

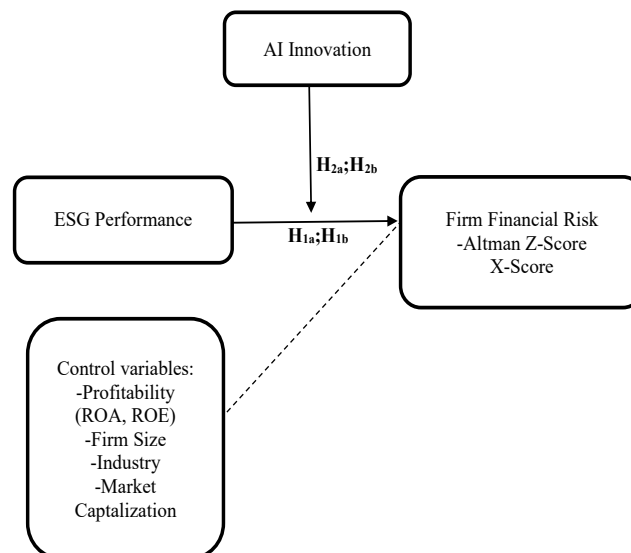


Figure 1. Conceptual Framework

METHODS

This research uses a quantitative approach with panel data methods to analyze the impact of ESG performance on companies' financial risk, as well as to examine the moderating role of AI innovation. The data used are secondary data collected from various sources. The ESG score was obtained through the LSEG database, and the control variables came from companies' financial reports, while the AI innovation data was obtained from <https://pdki-indonesia.dgip.go.id>. The study population includes all companies listed on the Indonesia Stock Exchange (IDX) during the period 2018–2024. The sampling technique used is purposive sampling, with criteria being companies that have ESG information and complete study data during the observation period.

Data analysis was done using panel regression with the Fixed Effect Model (FEM) because this model can control for unobserved differences in characteristics between companies and across observation periods that could affect financial risk. The study also applied Industry FE and Year FE to account for differences in industry sector characteristics and changes in economic conditions each year. The analysis steps included descriptive statistics, Pearson correlation, and hypothesis testing using regression with a moderating variable, which is AI innovation to examine interaction effects. A clearer explanation of the sample is described in Table 1. The ESG score here is used as the overall value of each company's ESG performance and serve as independent variable.

Table 1. Sampling Breakdown

DESCRIPTION	TOTAL
Total companies listed on IDX	941 Company
Total companies that have ESG data	80 Company
Companies with ESG data in 2018	17 Company
Companies with ESG data in 2019	33 Company

Companies with ESG data in 2020	39 Company
Companies with ESG data in 2021	56 Company
Companies with ESG data in 2022	65 Company
Companies with ESG data in 2023	65 Company
Companies with ESG data in 2024	65 Company
Total company year observations	340 Company

Table 1. Sampling Breakdown shows the process of selecting research samples from the initial population until the final number of observations used in the analysis is obtained. The research population consisted of 941 companies listed on the Indonesia Stock Exchange (IDX). However, not all companies could be used as samples because this study requires companies to have ESG data during the observation period.

Based on the screening process, 80 companies were found to have ESG data and meet the research criteria. The number of companies with ESG data has increased from year to year, with 17 companies in 2018, 33 companies in 2019, 39 in 2020, 56 in 2021, and 65 in 2022 - 2024. This increase indicates that ESG implementation and reporting in Indonesia are growing as companies pay more attention to sustainability practices.

The number of observations in the study is calculated based on the concept of firm-year observations, meaning each company observation in a period is counted as one observation. So, the total number of observations collected from 2018 to 2024 is 340 firm-year observations. The variation in the number of companies each year shows that the study uses unbalanced panel data, because not all companies have consistently available data throughout the observation period.

Tabel 2. Variable Definition and Measurement

VARIABLE	DESCRIPTION	SOURCE
Altman Z-score	Indicators used to predict the potential bankruptcy of a company	(Altman, 2007; Fu et al., 2024)
Zmijewski X-score	Financial distress measurement using profitability, leverage, and liquidity	(Nerotumilena & Winarna, 2024)
Environmental, Social, Governance performance (ESG performance)	ESG practice scores obtained through LSEG Database	(Agustín et al., 2025; Agustín & Safitri, 2025)
AI innovation	The level of AI innovation is measured using the logarithm (1 + number of AI patents) as a way to show how intensively companies are developing AI	(Liu et al., 2025a)
Profitability (ROA, ROE)	Profitability ratio is measures the company's ability to generate profits from assets as well as its effectiveness in generating a net profit from stakeholder equity	(Arbelo et al., 2021)
Firm size	The size of the company is assessed from the logarithm of total assets	(Valencia, 2025)
Industry	Segmentation of companies by type of business so that it reflects operational characteristics	(Drori, 2026)
Market capitalization	The market value of a company calculated from the share price multiplied by the number of outstanding shares of the company	(Kumar et al. 2020)

The dependent variable of this research is firm financial risk, which uses Altman Z-Score and Zmijewski X-Score as measurements of firm financial risk. These two measurements are widely used in previous studies to represent firm financial risk and bankruptcy potential (Azam et al., 2023; Cındık & Armutlulu, 2021; Mavengere & Gumede, 2024). The Z-Score predicts short-term bankruptcy risk using several financial ratios, where lower values indicate higher financial risk and higher value reflect better financial stability (Spulbar, 2025). Meanwhile, the X-Score measures the profitability of financial distress where value > 0 indicates potential bankruptcy risk, while values < 0 indicate healthier financial conditions (Martini et al., 2023). Both measurements are calculated using the following format:

$$Z - Score_{it} = (1.2 \text{ Working Capital} + 1.4 \times \text{Retained Earnings} + 3.3 \times \text{Earnings Before Interest and Taxes} + 0.999 \times \text{Sales Revenue})$$

$Z - Score_{it}$ represents the company's Z-Score calculation for each year of observation. The model combines Working Capital, Retained Earnings, Earnings Before Interest and Taxes (EBIT) and Sales Revenue to evaluate the company's financial condition and predict the likelihood of bankruptcy (Altman, 2007; Fu et al., 2024).

$$X - Score_{it} = -4.3 - 4.5 X1 + 5.7 X2 - 0.004 X3$$

X1 represents profitability measured by ROA, X2 represents leverage measured by the ratio of total debt to total assets, while X3 represents liquidity measured by current ratio (Nerotumilena & Winarna, 2024). Furthermore, this study adopts AI innovation as a moderating variable, which refers to artificial intelligence-based innovation used by companies to improve operational efficiency, data analysis, and decision-making quality. AI innovation is measured using the number of AI technology patents owned by the company, as patents represent the tangible output of Research and Development (R&D) activities and indicate a company's capability to develop and protect AI innovation (Ni et al., 2026; Ponta et al., 2021). Higher patent values reflect stronger AI innovation capabilities, while lower value indicate limited AI technology utilization within the company.

The innovation in AI in this research is approached by looking at the number of patents based on Artificial Intelligence (AI) that the company owns. Using patents as a proxy is based on previous research that considers patents as a representation of a company's technological innovation capacity and knowledge accumulation. The number of patents reflects the company's ability to utilize AI, so it can be used to measure the level of technological innovation of the company. However, this indicator represents more the innovation capacity than the direct operational implementation of AI. Considering that AI patent ownership in Indonesia is still relatively limited, this measurement has its limitations because it still doesn't fully reflect the intensity of AI use in companies' operational activities (Hött et al., 2025).

After defining all the research variables and determining their measurement methods, the next step is to process the data before estimating the model. This stage aims to ensure that the data used is of adequate quality so that the analysis results can provide more accurate estimates. In research using financial data from companies, extreme values (outliers) are common due to differences in company characteristics, variations in company size, and the dynamics of financial performance during the observation period (Linares-Mustarós & Farreras-Noguer, 2022). If not handled properly, outlier values can affect the data distribution and cause distortions in the results.

Therefore, this research applies the winsorization technique to continuous variables as part of the data processing before testing the model. The winsorization technique is carried out by capping the values of observations at the lower and upper limits of the data distribution according to percentiles (1% and 99%), so that extreme values can be adjusted without removing observations from the research sample. This approach was chosen because it can reduce the impact of outliers on the estimation results while still keeping the number of observations representative. Once the data processing is finished, the hypothesis test is carried out using a panel regression model (Ismadyaliana et al., 2024; Jiao & Pretis, 2022).

Model Specification

The regression model used in this study can be formulated as follows:

$$Z - Score_{it} = \beta_0 + \beta_1 ESG\ Score_{it} + \beta_2 Controls_{it} + \sum YEAR + \varepsilon_{it} \dots (1)$$

$$X - Score_{it} = \beta_0 + \beta_1 ESG\ Score_{it} + \beta_2 Controls_{it} + \sum YEAR + \varepsilon_{it} \dots (2)$$

$$Z - Score_{it} = \beta_0 + \beta_1 ESG\ Score_{it} + \beta_2 AI_{it} + \beta_3 (ESG * AI) + \beta_4 Controls_{it} + \sum YEAR + \varepsilon_{it} \dots (3)$$

$$X - Score_{it} = \beta_0 + \beta_1 ESG\ Score_{it} + \beta_2 AI_{it} + \beta_3 (ESG * AI) + \beta_4 Controls_{it} + \sum YEAR + \varepsilon_{it} \dots (4)$$

Z-Score and X-Score is used to measure firm bankruptcy risk with ESG as the independent variable ε_{it} representing error term. This study applies 4 regression models. Models (1) and (2) for test the influence ESG performance to firm financial risk with the hypothesis (H_{1a}) and (H_{1b}), while models (3) and (4) to assess the moderating role of AI innovation in relationship between ESG performance and financial risk by using Z-Score and X-Score (H_{2a}) and (H_{2b}).

RESULT

Table 3 presents the descriptive statistics for each variable examined.

Table 3. Descriptive Statistics Results

	N	Mean	Standard Deviation	Minimum	Maximum
Z-Score	340	5.449	39.319	-1.969	607.944
X-Score	340	-2.674	1.529	-6.492	3.176
ESG score	340	52.833	19.380	9.865	88.880
AI innovation	340	2.773	1.290	0.693	6.395
Market cap	340	1.629e+13	8.869E+13	27.570	1.193e+15
Firm size	340	31.736	1.354	28.378	35.315
ROA	340	0.064	0.075	-0.090	0.557
ROE	340	0.161	0.289	-0.756	2.165
SIC	340	5.526	3.199	1.000	11.000

Source : Author's Calculation (2026)

The descriptive statistics consist of 340 observations and provide an overview of the data distribution. The Z-Score mean of 5.45 with very high standard deviation of 39.32 and range from -1.97 to 607.94. In contrast, the X-Score shows a more stable distribution, a mean of -2.67, and standard deviation 1.53 value ranging from -6.49 to 3.18. The ESG score has a mean 52.83 with standard deviation of 19.38, reflecting variation in ESG performance among companies. Meanwhile, AI innovation has a mean of 2.77 with a standard deviation of 1.29 and ranges from 0.69 to 6.40, indicating moderate variation in AI innovation across the sampled companies. Market capitalization shows that the mean is high and the standard deviation is also high, which means there is a significant difference in company market size, while firm size is relatively more homogeneous based on total assets. Profitability variables also show variation among companies, where ROA has a mean of 0.064 and a standard deviation of 0.075, which indicates a difference in the company's ability to generate profits. ROE has a mean of 0.161 and a standard deviation

of 0.289, indicating differences in companies ability to generate profits and returns on equity (Nurjanah et al., 2021).

Table 4. Pearson Correlation Results

Variable	Z-Score	X-Score	ESG score	AI innovation	Market cap	Firm size	ROA	ROE	SIC
Z-Score	1.000								
X-Score	-0.049 (0.368)	1.000							
ESG score	0.093* (0.088)	-0.317*** (0.000)	1.000						
AI innovation	0.016 (0.774)	-0.057 (0.292)	-0.096* (0.076)	1.000					
Market cap	0.678*** (0.000)	-0.059 (0.280)	0.170*** (0.002)	0.003 (0.962)	1.000				
Firm size	0.075 (0.166)	-0.195*** (0.000)	0.413*** (0.000)	-0.151*** (0.005)	0.270*** (0.000)	1.000			
ROA	-0.010 (0.855)	-0.386*** (0.000)	0.152*** (0.005)	0.053 (0.331)	-0.033 (0.549)	- (0.000)	1.000		
ROE	0.011 (0.835)	-0.099* (0.067)	0.250*** (0.000)	0.020 (0.713)	0.025 (0.643)	-0.042 (0.438)	0.437*** (0.000)	1.000	
SIC	-0.081 (0.135)	0.210*** (0.000)	- (0.000)	0.181*** (0.001)	-0.099* (0.069)	- (0.000)	0.040 (0.464)	-0.060 (0.273)	1.000

Source : Author's Calculation (2026)

Table 4 shows the Pearson correlation analysis between the variables to provide the initial relationship between two variables. The Z-Score has a significant positive correlation with market capitalization, indicating that companies with large market capitalization will have better financial health. Meanwhile, the relationship between Z-Score and ESG is fairly significant at 10% level. However, the X-Score shows several significant relationships, including strong negative correlation with ESG, ROA, and firm size, indicating that higher X-Score values are associated with lower values of these variables. The X-Score also has a significant positive correlation with SIC, while its relationship with ROE is only weakly significant (Hung et al., 2017). ESG shows a significant relationship with several variables, where larger and more profitable companies tend to have better ESG performance. ESG also has a weak signif

icant with AI innovation and strong significant with SIC. Meanwhile, AI innovation is significantly correlated to firm size and SIC, but not to market capitalization, ROA or ROE, indicating that AI innovation is more related to company size and industry sector than to financial performance. In addition, market capitalization has a strong significant with firm size, while ROA and ROE are also strongly significant positively correlated, showing that companies with high profitability tend to generate high returns on equity (Ariani et al., 2025; Aydoğmuş et al., 2022).

Table 5. Regression Tests Analysis

Variable	Model 1 Z-Score	Model 2 X-Score	Model 3 Z-Score	Model 4 X-Score
ESG score	0.044 (1.53)	-0.015*** (-3.73)	0.159** (2.01)	-0.027*** (-3.17)
AI innovation			1.966** (2.11)	-0.358*** (-2.74)

ESG*AI			-0.038** (-2.10)	0.004 (1.59)
Market cap	0.000** (2.01)	-0.000** (-2.34)	0.000** (2.02)	-0.000** (-2.34)
Firm size	-1.661** (-2.22)	-0.173*** (-2.88)	-1.669** (-2.25)	-0.180*** (-3.05)
ROA	-0.732 (-0.08)	-9.997*** (-8.22)	-1.644 (-0.18)	-9.723*** (-8.23)
ROE	-0.906 (-0.69)	0.752* (1.79)	-1.120 (-0.82)	0.800** (2.01)
_cons	58.824** (2.28)	3.785* (1.96)	52.930** (2.26)	4.987*** (2.62)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
r2	0.251	0.356	0.255	0.380
r2_a	0.223	0.332	0.223	0.353
N	340	340	340	340

Source : Author's Calculation (2026)

The results of the regression test provided in table 5 show that the influence of ESG on the firm financial risk produces different findings depending on the risk measure used. In Model 1, ESG doesn't show a significant effect on the Z-Score, which indicates that implementing ESG hasn't yet managed to directly improve the company's financial stability in the short term, since applying ESG usually requires a relatively large initial investment, like operational transformation costs, strengthening governance, and implementing sustainability practices, so the economic benefits aren't fully reflected in the company's operational health indicators yet (Abdi et al., 2022). This condition is in line with the RBV theory perspective, which explains that the investment will generate a competitive advantage and economic value after going through the process of resource accumulation and the formation of the company's capabilities. (Novitarini & Sudana, 2024). This finding is also consistent with previous research that found that the influence of ESG on financial stability tends to be seen more in the long term than in the short term. (Handoyo, 2026). According to the test results, hypothesis H_{1a} wasn't supported because no significant effect was found.

On the other hand, in model 2 shows that ESG has a significant negative effect on X-Score, which indicates that improving ESG performance is related to a decrease in financial distress risk. These results support stakeholder theory, which says that ESG practices boost a company's legitimacy through greater transparency, better governance, and stakeholder trust, which can strengthen the company's financial resilience. Companies with good ESG performance tend to get more stable access to financing, relatively low initial capital costs, and a better ability to mitigate risks (Alduais, 2023). These findings are in line with Hoepner et al. (2024) which shows that companies with high ESG performance have a lower chance of bankruptcy and financial stress. So, hypothesis H_{1b} has been empirically supported. The difference in results between Z-Score and X-Score also shows that both indicators capture different risk dimensions, with Z-Score being more sensitive to the company's operational stability, while X-Score puts more emphasis on the likelihood of financial trouble.

In models 3 and 4, AI innovation shows a different effect on the firm financial risk. AI has a weak positive effect on the Z-Score and a significant negative effect on the X-Score, which indicates that AI innovation can improve operational efficiency and strengthen the company's ability to manage risk. (Chen et al., 2022). However, the interaction between ESG and AI shows a weak positive effect on the Z-Score and no

significant effect on the X-Score, indicating that AI has not yet managed to consistently strengthen the relationship between ESG and financial risk. This situation may happen because implementing ESG and digital transformation at the same time requires a considerable initial investment, so their synergistic benefits have not yet been fully realized during the observation period. These findings are in line with Luo (2025) which indicates that the integration of ESG and AI still faces challenges in adoption levels and organizational readiness that vary across companies. Therefore, even though the ESG and AI interaction has a significant impact on the Z-Score, the direction of the effect doesn't match the hypothesis, so hypothesis H_{2a} is not supported, and hypothesis H_{2b} also doesn't get empirical backing.

DISCUSSION

The research results show that the impact of ESG performance on a firm financial risk gives different results depending on the indicator used. ESG performance doesn't show a significant effect on financial stability when measured with Z-Score, but it can significantly reduce the risk of financial distress when measured with X-Score. These findings indicate that the impact of implementing ESG doesn't always appear simultaneously across all dimensions of financial risk and can be influenced by the characteristics of each indicator.

The insignificant positive result on the Z-Score suggests that the benefits of ESG have not fully materialized during the study period. ESG implementation requires substantial initial costs, including sustainability reporting, eco-friendly investments, governance development, and operational transformation, which may create short-term financial pressure before long-term benefits are achieved (Riegler, 2025). These findings are in line with August et al. (2025) that show the influence of ESG on firm stability is more evident in the long-term than short-term. This finding is in line with the RBV theory, which explains that strategic resources can only create economic value after a company manages to accumulate capabilities and integrate them into its operations. In this context, ESG can be seen as an intangible resource that needs time before it can generate competitive advantages and financial benefits (Bhandari, 2022).

In contrast, that negative significant result on X-Score indicating that companies with better ESG tend to have lower financial distress. These results show that implementing ESG directly helps lower the risk of bankruptcy by improving transparency, governance quality, corporate reputation, and investor confidence. Corporations with high ESG also have better access to financing, supporting the findings of Gao et al. (2025) where companies with high ESG rarely experience financial distress and bankruptcy risk. Therefore, ESG implementation, which requires significant upfront investment, often does not yet have an immediate impact on short-term operational stability, as reflected in the Z-Score, but can more quickly influence in reducing the financial distress, as reflected in the X-Score. These results are in line with previous research that found that companies with high ESG performance are less likely to go bankrupt and have more stable financial conditions (Hoepner et al., 2024). These findings support stakeholder theory, which explains that companies can create long-term value through their ability to meet stakeholders' expectations and maintain legitimacy through responsible business practices. Companies that perform well in ESG tend to have strong relationships with investors and other stakeholders, which can reduce uncertainty and boost the company's financial resilience (Sandberg, 2023).

The difference in regression result between the Z-Score and the X-Score comes from the fact that the two models use different approaches to measure risk. The Altman Z-

Score focuses more on a company's ability to maintain operational stability and overall business health through a combination of liquidity, profitability, activity, and leverage ratio (Kamal & Visita, 2020). Meanwhile, the Zmijewski X-Score focuses more on profitability when facing financial distress, based on the company's leverage, profitability, and liquidity indicators (Arifuddin et al. 2023). Therefore, the benefits of ESG seem to show up faster in reducing financial distress than in improving overall operational stability.

Also, the results of the moderation analysis show that AI innovation hasn't yet been able to consistently strengthen the impact of ESG on a firm financial risk. While AI does directly help improve operational efficiency and decision-making quality, the interaction results show that just having AI isn't enough to boost the benefits of ESG for a company's financial stability. These findings suggest that the relationship between ESG and a firm's financial risk doesn't rely only on having the technology, but also on the company's ability to effectively integrate it into their sustainability strategy.

Theoretically, companies with high ESG and backed by AI should have a better ability to maintain financial stability and reduce the risk of financial trouble (Citterio & King, 2023). However, the results of this research show that this mechanism has not yet fully taken place in Indonesian companies during the observation period. One possible reason is that AI and ESG are complementary capabilities, so the benefits of both only show up after the company has organizational readiness, good data governance, HR skills, and an adequate level of digital maturity. When the company is still in the early stages of transformation, investing in AI can even increase operational complexity and implementation costs, so it doesn't yet have a positive effect on the relationship between ESG and the firm financial risk. This finding is in line with the RBV perspective, which emphasizes that technology doesn't create a competitive advantage on its own, but needs to be combined with other resources and capabilities to generate economic value. (Bhandari, 2022). Therefore, the fact that the role of AI moderation is not significant in this research indicates that the integration between ESG strategy and digital transformation is still in a developmental stage and isn't yet mature enough to consistently impact reducing the firm financial risk.

CONCLUSION

This research aims to analyze the impact of ESG performance on companies' financial risk and examine the moderating role of AI innovation in companies listed on the IDX. The results show that ESG has different effects depending on the financial risk indicator used. ESG does not have a significant effect on financial stability measured by the Altman Z-Score, which indicates that the benefits of implementing ESG are not yet fully reflected in the company's short-term operational stability, as initial investments and a capacity development process are required. However, ESG has been shown to reduce company financial risk when measured with the Zmijewski X-Score. This finding suggests that ESG practices are more effective at strengthening a company's resilience to financial distress risk than at directly improving operational stability. Also, innovation in AI shows a contribution to improving companies' financial conditions through operational efficiency and strengthening risk management capabilities. However, the moderating role of AI in reinforcing the relationship between ESG and a firm financial risk has not yet shown consistent results. These findings indicate that AI alone is not enough to increase the financial benefits of implementing ESG without the support of organizational readiness, digital maturity, and effective integration between sustainability strategy and digital transformation.

Practically, the results of this research show that companies shouldn't evaluate ESG implementation just based on short-term financial indicators. The benefits of ESG tend to be more evident in the form of reduced risk of financial troubles and strengthening the long-term sustainability of the business. Also, implementing AI needs to be accompanied by company preparedness and an implementation strategy to be able to create added value in the company's sustainable performance. However, this research still has some limitations. First, the observation period is relatively short, so it hasn't been able to fully capture the long-term benefits of ESG. Second, the number of samples is limited because not all companies have complete ESG data available. Third, the measurement of AI innovation only uses the number of AI patents as an indicator, so it still doesn't fully represent the level of digital transformation and the actual use of AI in companies. Therefore, it is suggested that future research use a longer observation period to better capture the long-term impacts of ESG, expand the sample coverage across different sectors and countries, and use more representative AI measurements, such as the level of AI adoption, technology investment, digital maturity, or organizational readiness for digital transformation.

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