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Abstract

The primary goal of the study is to evaluate the effectiveness of our AI-based greenwashing detection. The effectiveness test was conducted by examining (1) Is there a difference between greenwashing scores using AI-based greenwashing detection (AI-GW) and a database? (2) Does using data from AI-GW and databases produce the same results regarding whether greenwashing affects performance? We use Stata 15.1 analysis in a panel data structure to test the hypotheses. This study found that there was no difference between greenwashing scores based on our AI-GW and those using a database. This study also found a positive correlation between AI-GW and greenwashing scores from a database. The findings show that greenwashing has a negative significant effect on financial performance, consistent across both our AI-GW-derived scores and database-derived data.

***Key words*:** Greenwashing, artificial intelligence, ESG

1. Introduction

Environmental problems—including habitat destruction, pollution, ozone depletion, climate change, and resource constraints—have a significant impact on environmental degradation (Dijoo & Khurshid, 2022). Companies are under increasing pressure to make environmentally friendly efforts due to the growing number of environmental problems in the world and the belief that business has a significant role to play in addressing these problems (Pan et al., 2020). As a result, businesses have a strong incentive to tell stakeholders that they conduct business sustainably (Berrone et al., 2017; Quintana-García et al., 2021). Studies reveal that some businesses are responding to public pressures on environmental issues by proposing substantial improvements to their environmental performance (Weaver et al., 1999). However, as noted in the literature (e.g. Amores-Salvadó et al., 2022; Berrone et al., 2017; W. Li et al., 2022; Walker & Wan, 2012), some businesses react symbolically, offering little to no change, or participating in greenwashing. Greenwashing arguably gives a wrong message to stakeholders (Walker & Wan, 2012) and causes environmental exploitation. However, currently, there is still little research that uses technology-based detection methods to detect greenwashing practices. We argue that the use of advanced technologies can help detect greenwashing. Therefore, stakeholders have well informed decisions to support or not to support companies' operations.

In this paper, ESG greenwashing is defined as the difference between "substantive" and "symbolic" corporate environmental, social, and governance activities (see Lyon & Montgomery, 2015; Walker & Wan, 2012). Firms that conduct symbolic activities do so in order to ceremonially adhere to social norms and expectations (Weaver et al., 1999; Zott & Huy, 2007). Symbolic acts have the power to strengthen an organization's legitimacy or reputation, which, in turn, elevates the organization's relationship with its values in a given cultural setting (Fombrun, 2005). A firm's measurable actions and actual resource investments are referred to as substantive actions (Weaver et al., 1999; Zott & Huy, 2007). Despite the fact that greenwashing has been the subject of some research (Lyon & Montgomery, 2015); Testa et al. (2018); Walker & Wan (2012); Schons & Steinmeier (2016) as well as Li et al. (2022), there has not been much focus on techniques of identifying greenwashing. In addition, most previous studies focus on the gap between environmental performance and environmental disclosure, ignoring social and governance aspects.

Currently, greenwashing measurements use manual content analysis (W. Li et al., 2022) and extracted from specific databases (X. Du et al., 2018; Guix et al., 2022; Huang et al., 2022; Khalil & O'sullivan, 2017; Kim & Lyon, 2015; Marquis et al., 2016; Neumann, 2021; Roulet & Touboul, 2015; Testa et al., 2018; Velte, 2021; Walker & Wan, 2012; Yu et al., 2020; D. Zhang, 2022). However, both of these measurements have weaknesses. Content analysis cannot determine the truth of a statement or evaluate the quality of a report. Content analysis is able to reveal the content in the text but cannot interpret the significance of that content (Neuman, 2014).

The use of data from databases to measure ESG greenwashing also has weaknesses: First, low coverage of ESG score data and ESG disclosures in empirical analysis in several countries. For example, Chen et al. (2024) state that approximately 3,800 firms are listed in Japan, but, as of 2019, Thomson Reuters only rate about 430 companies or around 11% of the total population. This low coverage will create difficulties in decision-making for stakeholders, especially in developing countries. The low level of law enforcement in developing countries causes low quality of company information (Su et al., 2016). This causes uncertainty in the assessment and evaluation of the company's environmental performance (Wei et al., 2017). The low quality of information and the limitations of stakeholders in processing sustainability information cause stakeholders to be unable to identify and punish greenwashers (W. Li et al., 2022). Therefore, in developing countries, a greenwashing detection model with high coverage is needed which is useful for various parties, banking parties for example, need this model to provide credit contraints for companies with poor environmental performance (Gong et al., 2020) to increase green financial inclusion (Wang et al., 2022).

Second, there is controversy over ESG scores from different rating agencies. Although there are many ESG rating agencies worldwide Kinder, Lydenberg, and Domini (KLD), Sustainalytics, Moody's ESG (Vigeo-Eiris), S&P Global (RobecoSAM), Refinitiv (Asset4), and MSCI, research has found that there are contradictions in ESG scores among rating agencies. In some cases, ESG rating agencies give different or even contradictory ratings to the same company (Berg et al., 2022). To address the above issues, we apply AI, particularly natural language processing, to create our unique ESG scores and ESG disclosure to detect greenwashing.

In spite of the fact that environmentally friendly measures may conflict with the organization's primary purpose of raising profits and so negatively damage the company's financial performance, companies have experienced pressure to operate sustainably. Numerous studies indicate that environmental initiatives raise operating costs for companies (Aldy & Stavins, 2012; Nordhaus, 2007; Stern, 2008). Further research indicates that environmental measures implemented by firms may yield unusually poor returns (Hilton, 2025). The growing institutional constraints for environmentally conscious organizations force managers to make trade-offs between market and environmental logics (Dahlmann & Grosvold, 2017). If being environmentally conscious does not necessarily convert into higher share value, then greenwashing might be a good strategy for managing the tension between environmental concerns and shareholder demands (Carmichael et al., 2022). Organizations can resolve logical disagreements through the separation of symbolic from substantive acts (Greenwood et al., 2011; Lyon & Maxwell, 2011).

As currently understood, there is no conclusive evidence that greenwashing has an impact on performance. W. Li et al. (2022) found that greenwashing and financial performance were positively correlated. However, Testa et al. (2018) find that greenwashing had no influence on the performance of businesses. But as X. Du (2015), Testa et al. (2017, 2018) showed, using greenwashing techniques might have unfavorable effects on the market response. An empirical study by Walker & Wan (2012) suggests that using greenwashing tactics has a detrimental effect on financial performance. Neumann (2021) finds that whereas green highlighting led to a minor improvement in performance, startups that used a greenwashing strategy observed a decline in performance. Meanwhile, Birindelli et al. (2024) find that greenwashing had a detrimental effect on performance. This difference in results may be due to the different greenwashing measures used. Disagreements in ESG ratings among rating agencies cause complicate ESG performance assessment (G. Li & Cheng, 2024).

Therefore, the goal of the study is to evaluate the effectiveness of our AI-based greenwashing detection. The effectiveness test is conducted by by posing two questions. (1) Is there a difference between the greenwashing score using AI-GW and database-based data? (2) Does using data from AI-GW and databases produce the same results with regard to whether greenwashing affects performance? More specifically, this research differs from previous research in that: First, previous research measuring environmental performance and communication used manual content analysis from companies' websites (Walker & Wan, 2012), and secondary data from databases (X. Du et al., 2018; Huang et al., 2022; Neumann, 2021; Testa et al., 2018; Yu et al., 2020). This research uses AI-based greenwashing detection (AI-GW) developed by Sari et al., 2023. AI is believed to be able to reveal hidden insights from data, closer to real-time (Jovanovic et al., 2022) and can potentially improve decision-making significantly (Duan et al., 2019). Second, this research compares the use of AI-GW to the use of databases in greenwashing detection. This comparison is used to test the effectiveness of the AI-based detection model. This research is different from Chen et al. (2024) who recently used AI in measuring ESG performance while this study also measured ESG communication and greenwashing. To the best of our knowledge, this paper is the first comprehensive study to examine the use of AI-based data to detect greenwashing and compare the results of the relationship between greenwashing and performance using AI-based data and the use of databases.

We consider Indonesia as the right field to test the effectiveness of AI-GW score and the influence of greenwashing on performance because: First, the low coverage of ESG score and ESG performance data. Data from 2017-2022, there are 3759 companies, but only 272 (7.2%) have ESG Score data and 238 (6.3%) ESG disclosure. Second, ESG rating disagreements are more pronounced for companies in the Asia Pacific region than in Europe and North America (Boucher et al., 2021). Third, Indonesia is the 14th most polluted country based on the World Air Quality Report (IQAir, 2024). This greenwashing detection is expected to provide a performance assessment that is open to the public so that it can encourage companies to further improve their environmental performance.

2. Literature Review and Hypotheses Development

2.1. AI-based greenwashing detection (AI-GW)

2.1.1. Existing studies

Numerous studies have previously examined the causes of greenwashing and how it affects financial choices. Unfortunately, a crucial problem with the numerous studies on greenwashing is still how to accurately measure it. Bernini et al. (2023) examine the many approaches that have been employed to quantify greenwashing. The first of these methods is perception (Y.-S. Chen & Chang (2013), De Vries et al. (2015), Leonidou & Skarmeas (2017), L. Zhang et al. (2018). Second, the difference between the environmental performance index and the disclosure index. The majority of the examples are taken from particular databases, such as Asset4/Thomson Reuters or Bloomberg. Third, economic model (X. Du, 2015).

Additionally, Z. Chen et al. (2024) Recently employed AI to gauge Japanese corporations' ESG performance.

2.1.2. Hypotheses development

This study employs artificial intelligence (AI) to detect greenwashing. Chen et al. (2024) found that AI-based ESG Score is positively correlated with ESG Score by Thomson Reuters (Refinitiv). The study also found that ESG firms have higher firm value, this result is consistent with both using AI-based ESG Score and Thomson Reuters (Refinitiv). This shows the validity of the AI-based ESG Score measurement method. To test the accuracy of AI-GW, we compare greenwashing detection using data from AI and Thomson Reuters/ Bloomberg databases. We propose a hypothesis.

H_1: There is no difference in greenwashing scores using database-based and AI-GW data

2.2 Greenwashing and Corporate Financial Performance

2.2.1. Existing studies

Voluntary environmental disclosure means that the content of reports largely depends on corporate policies, with well-performing companies likely to report positive sustainability performance, while those performing poorly may conceal it (Christensen et al., 2021). The second action is commonly referred to as greenwashing (Delmas & Burbano, 2011; W. Li et al., 2022). Essentially, greenwashing is about "lip service," where this action is associated with exaggerated disclosure of ESG performance that is not actually carried out.

There are two reasons why businesses participate in greenwashing. Firstly, according to Oliver (1991), legitimacy must be attained. Second, in line with the signaling theory (Connelly et al., 2011), corporations usually utilize symbolic communication to communicate to external stakeholders their opinions regarding environmental issues (Ramus & Montiel, 2005). Managers may prioritize symbolic statements and acts above substantive or real action on environmental issues since doing so is easier and less expensive than implementing green principles (Suchman, 1995).

As of now, there is no conclusive evidence of whether greenwashing has an impact on performance. Li et al., (2022) and Schons & Steinmeier (2016) found a positive impact between greenwashing on financial performance. This is justified by the market's asymmetric information (Schons & Steinmeier, 2016), stakeholders' limited access to information, and a lack of professional knowledge to understand environmental performance disclosures (Parguel et al., 2015), causing a misjudgment of greenwashing. However, Testa et al. (2018) found that greenwashing had little impact on the performance of businesses.

Businesses may claim to be green in order to benefit from symbolic greening measures without having to pay for real, significant work (Walker & Wan, 2012). Other studies, however, have found that greenwashing worsens financial performance (Darendeli et al., 2022; Walker & Wan, 2012). When a corporation made misleading claims about being environmentally friendly, the market became enraged, as shown by Du (2015), which caused confidence to drop and stock prices to drop. Greenwashing causes customers to become confused and doubtful (Leonidou & Skarmeas, 2017).

2.2.2. Hypotheses development

Stakeholders may begin to detect a disconnect between environmental communication and practice. In this case, greenwashing will be penalized, which will reduce the market value and profitability of the company. The process of gaining legitimacy concludes with the loss of legitimacy, which has a negative impact on corporate performance. The use of greenwashing strategies has detrimental effects on the market (X. Du, 2015; Testa et al., 2017, 2018). Thus, this can reduce the support and loyalty of stakeholders (Schons & Steinmeier, 2016) and lead to market penalties (X. Du, 2015). Walker & Wan (2012) have found empirical evidence that the use of greenwashing techniques has a negative effect on financial performance, while Neumann (2021) finds that startups that use a greenwashing strategy perform worse. Birindelli et al. (2024) find that greenwashing has a negative effect on performance.

The risks associated with greenwashing have been explored in previous studies (X. Du et al., 2018; Scheidler et al., 2019). Thus, if symbolic greening strategies are not backed by real actions, they have a detrimental impact on business performance due to the serious risk of exposure. The company's brand and investor trust are harmed by greenwashing, which can also lead to a decline in financial performance. Customers may also lose trust in a product and grow wary of companies that engage in greenwashing. As a result, consumers may choose not to purchase the product altogether (Braga Junior et al., 2019). Therefore, the first hypothesis of this study asserts that:
H2: Greenwashing has a negative effect on financial performance.

3. Data and Mthodology

3.1.Data

There are two types of data used in environmental performance assessment and environmental communication: First, data originating from Thomson Reuters and Bloomberg. Second, AI-based data that we automatically quantify using AI. This research uses AI-based greenwashing detection (AI-GW) which was developed by Sari et al. (2024). AI-GW has obtained copyright from the Ministry of Law and Human Rights of the Republic of Indonesia number 000637587. AI-GW application display appears in the appendix. Referring to the AI domain classification (Roundy & Asllani, 2024), the AI-based greenwashing detection uses the domains of natural language processing. The assessment of environmental performance scores, and environmental communication scores using input from financial reports, company websites and sustainability reports are the sources of data used in this study.

The data to be examined are from all companies (except those in the financial sector) that are listed on the Indonesia Stock Exchange (IDX) and have ESG scores and ESG disclosure data. The research period is from 2017 to 2022. Table 2 presents the total sample used.

Table 1. Total sample used

	Total Data From Database (2017-2022)	**Total data that has a complete ESG score and ESG disclosure (2017-2022)**	**Total data that has sustainability reporting, esg score and disclosure (2017-2022)**
Sektor	**firm year company**	**firm-year company**	**firm-year observation**
Basic Materials	394	29	20
Consumer Discretionary	858	31	17
Consumer Staples	487	45	27
Energy	242	30	28
Health Care	150	6	6
Industrials	837	33	30
Real Estate	466	25	13
Technology	132	1	1
Telecommunications	150	32	26
Utilities	43	6	6
Grand Total	**3.759**	**238**	**174**

Company data from Thomson Reuters and Bloomberg databases for the period 2017-2022 amounted to 3,759. Company data that have complete ESG disclosure and ESG score data amounted to 238. The data used for AI-based analysis comprise of 174 companies that have ESG scores, ESG disclosures, and complete sustainability reports for 2017-2022.

3.2.AI-based greenwashing detection (AI-GW)

The AI-GW uses the domains of natural language processing which has the capacity to recognize, process, or generate information from written or verbal human communication and the capacity to recognize and understand visual content, such as images and videos (Roundy & Asllani, 2024). Figure 1 presents the framework utilized in AI-based decision-making.

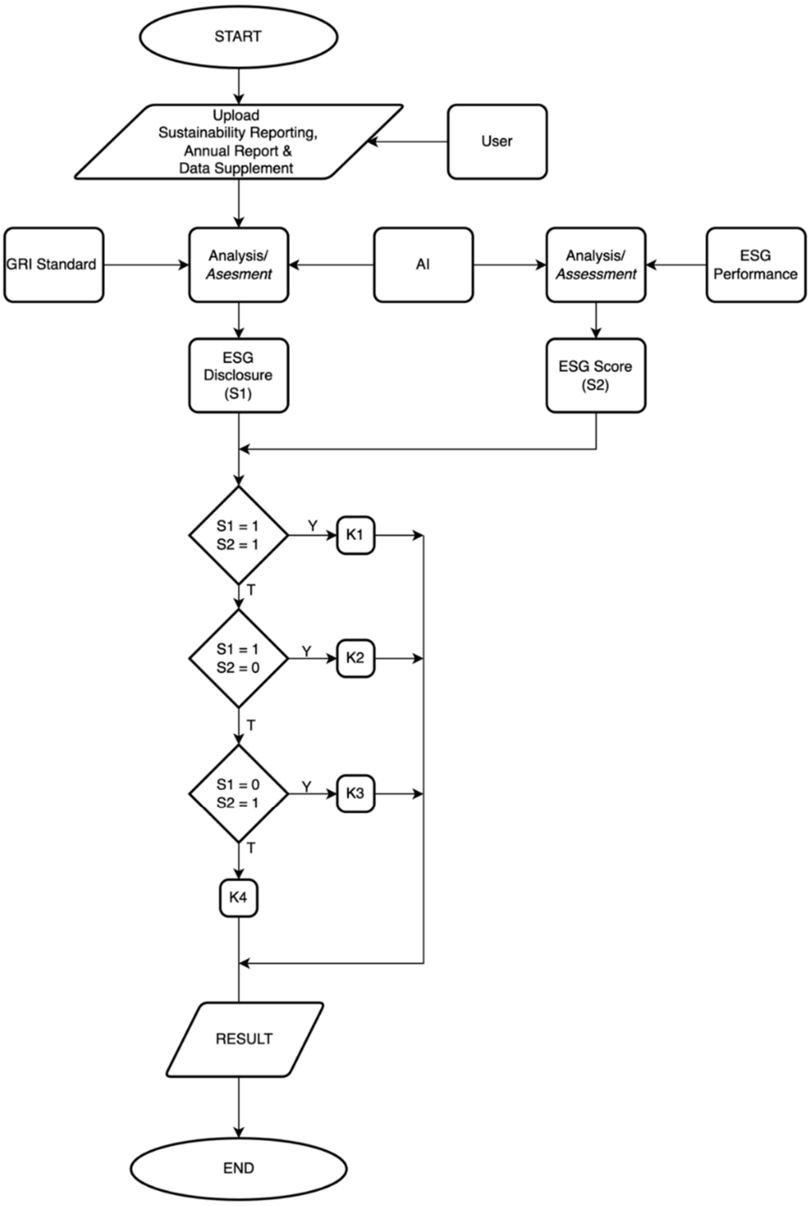

Figure 1. Frameworks Used in AI-based greenwashing detection (AI-GW)

Steps in a decision-making process using AI-GW:

a. Upload information from annual reports, sustainability reports, and other relevant reports.
b. Analysis or evaluation based on environmental performance and environmental communication indicators using artificial intelligence (AI). Sources of data from annual reports, sustainability reports, and news articles.
c. ESG disclosure is assessed based on environmental disclosure suitability based on GRI standards. ESG score is assessed based on environmental performance indicators.
d. Companies are categorized into greenwashing categories based on the scores produced in step c. If the ESG disclosure score (S2) > ESG Score (S1) then the company is classified as a greenwasher (K2).

3.3.Methodology

3.3.1. Research Variables

The research variables are environmental performance, environmental communication, financial performance and greenwashing. Environmental Communication is communication to provide information regarding environmental management efforts carried out by the company. Environmental communication was measured using ESG disclosure score from the Bloomberg databased, which consists of three different dimensions: environmental, social, and governance (W. Li et al., 2022; Testa et al., 2018) and AI-based ESG disclosure score. Environmental Performance is an assessment of company behavior to reduce the negative impact of business on the environment (De Jong et al., 2020; W. Li et al., 2022). Environmental performance is measured by the ESG score from Thomson Reuters and Bloomberg and AI-based ESG score.

Greenwashing is the selective disclosure of positive information about the company's environmental or social issues without fully disclosing negative information (Lyon & Maxwell, 2011). Greenwashing measurement uses a formula (W. Li et al., 2022) as follows:

$$GWI_{it} = \frac{(ECI_{it} - \overline{ECI})}{^{\sigma}ECI} - \frac{(EPI_{it} - \overline{EPI})}{^{\sigma}EPI}$$

ECI_{it} = Environmental communication of company i in year t.

EPI_{it} = Environmental performance of company i in year t.

$\overline{ECI}$ = Average environmental communication of sample companies

$\overline{EPI}$ = Average environmental performance of sample companies

$^{\sigma}ECI$ = Standard deviation of sample company environmental communication

$^{\sigma}EPI$ = Standard deviation of the sample company's environmental performance

The dependent variable of this study is firm performance. We measure firm performance using the MBV dan Tobin's Q.

Table 2. Summary of Variables' Measurements

Variables	**Type**	**Measurement**	**Source**
ROE	Dependent variable	Net Income / Shareholders' Equity	Birindelli et al. (2024); Hakimi et al. (2023); W. Li et al., 2022)
Tobin's Q	Dependent variable	Market Value of Firm / Replacement Cost of Firm's Assets	(Lu et al., 2021; Shah et al., 2023);
Greenwashing	Independent variable	Environmental commnunication – environmental performance	(W. Li et al., 2022)
Leverage	Control Variable	Total debt to total aset	(D. Zhang, 2022)
Size	Control Variable	ln(Total Assets)	(Hall & Weiss, 1967; Serrasqueiro & Maçãs Nunes, 2008)
Liquidity	Control Variable	current ratio (current asset to current liabilities)	(D. Zhang, 2022)
Board Size	Control Variable	Number of Board	(Akyildirim et al., 2023; P. Chen & Dagestani, 2023)

3.3.2. Hypothesis Testing

To test the hypothesis, we use model 1 using data from AI-GW and databases.

$$\boldsymbol{Performance_{it} = \alpha + \beta_1 Performance_{it-1} + \beta_2 GW_{it-1} + \beta_3\, Controls_{it} + e_{it}(1)}$$

The dependent variable is the company's performance. Performance is measured by accounting and market based performance. GW is the greenwashing score, C contains continuous control variables.

The robustness test is carried out by comparing the results of hypothesis testing using two different data sources: data originating from AI-GW and database data. This research refers to Chen et al. (2024) who tested the effectiveness of AI-based ESG scores by comparing the results of their research with data from existing rating agencies such as Refinitiv.

4. Results

Table 3 provides descriptive statistics of the variables used in this study including the greenwashing scores calculated with data from the database and AI-GW

Table 3. Descriptive statistics

Variable	Obs	Mean	Std. dev.	Min	Max
Dependent Variabkle					
ROE	174	0,300	0,389	-1,467	3,198
TobinQ	174	0,16	0,27	0,01	1,95
Independent Variable					
Databased greenwashing	174	0,014	0,807	-2,381	2,726
AI-Greenwashing	174	0,001	0,642	-2,625	1,261
Control Variable					
Leverage	174	0,264	0,188	0,000	0,811
Size	174	24,52	0,89	22,29	26,73
Liquidity	174	1,975	1,233	0,234	5,655
Board size	174	1,916	0,303	1,386	3,091

Table 4 shows the greenwashing scores per industry using data from AI-GW and databases.

Table 4. Greenwashing level across industry

	AI-GW greenwashing				Databased greenwashing			
Sector	Mean	Std. dev.	Min	Max	Mean	Std. dev.	Min	Max
Basic Materials	0,63	1,32	-0,88	2,59	0,56	1,00	-0,68	2,49
Consumer Discretionary	-0,10	0,32	-0,68	0,34	-0,11	0,83	-1,83	1,54
Consumer Staples	-0,11	0,43	-0,75	1,25	-0,06	0,70	-0,87	1,91
Energy	0,15	0,41	-0,72	0,90	0,07	0,53	-1,05	0,98
Health Care	0,22	0,25	-0,20	0,47	0,28	0,21	-0,61	-0,08
Industrials	-0,14	0,40	-0,86	0,73	-0,02	0,97	-1,41	2,76
Real Estate	-0,42	0,42	-1,27	0,21	-0,10	0,53	-0,95	1,01
Technology								
Telecommunications	-0,07	0,42	-0,71	1,01	-0,29	0,86	-2,35	1,32
Utilities	-0,29	0,36	-0,89	0,04	-0,76	0,30	-1,08	-0,37

Based on the results of Table 4, it shows that the industrial sectors with the largest greenwashing scores are the basic materials, energy, and healthcare industries.

4.1.1. Hypothesis Testing Results 1

Hypothesis 1 states that there is no difference in the results of greenwashing detection using Database ESG disclosure – performance score with AI-based ESG disclosure – performance score.

In this section, we test whether our AI-GW-based greenwashing score accurately captures the greenwashing phenomenon. To verify the validity of the AI-GW greenwashing score, which we have developed, we compare its rating to the Thomson Reuters and Bloomberg databases. We assume that the Thomson Reuters and Bloomberg greenwashing scores are appropriate to confirm the validity of the AI-GW score. If our greenwashing score (AI-GW) has no significant difference and is correlated with the Thomson Reuters and Bloomberg greenwashing scores, we can say that our AI-GW score has validity to detect greenwashing.

We used the paired t-test to test the difference in AI-GW and database scores, the results in Table 5 show that the average greenwashing score of AI-GW is 0.001 and for databases it is 0.014. The results of the average difference test show that there is no significant difference between the greenwashing scores of databased and AI-GW (p = 0.8611).

Table 5. Paired t-test

Variable	**Obs**	**Mean**	**Std. dev**	**Min**	**Max**
Databased greenwashing	233	0.014	0.807	-2.381	2.726
AI-GW greenwashing	174	0.001	0.642	-2.625	1.261

We also tested the correlation between the AI-GW and database-based greenwashing scores.

Table 6. Correlation between AI-GW and databased greenwashing score

	Databased greenwashing	**AI-GW greenwashing**
Databased greenwashing	1	
AI-GW greenwashing	0,235**	1
t statistics in parentheses** $p < 0.05$		

Table 6 shows the results of calculating the Pearson correlation coefficient between AI-based and database greenwashing scores. These results quantitatively show that the AI-GW and database greenwashing scores are positively and significantly correlated ($p < 0.05$). The small correlation between our AI-GW and the databased score supports the findings of Berg et al. (2022) who found that the average coefficient among six globally recognized ESG rating agencies was just 0.54. This is due to differences in measurement and weighting between rating agencies.

4.1.2. Hypothesis testing results 2

The System Generalized Method of Moments (GMM) approach is used in hypothesis testing. GMM is also used by Azmi et al., (2021) as the primary hypothesis test. Previous research has employed the system GMM technique (Blundell & Bond, 1998) to control endogeneity resulting from omitted variables (Bilgin, 2020). This is due to an endogeneity issue in the performance-greenwashing relationship. According to Zhang (2022), businesses experiencing financial difficulties are more likely to engage in greenwashing tactics. Businesses that are experiencing severe financial strain frequently implement particular financial tactics to safeguard their financial stability. Therefore, managers may reduce spending on sustainability initiatives while prioritizing achieving bottom-line targets that satisfy shareholder expectations. Preparers are also becoming more skeptical of the concrete effects of sustainability measures on a company's future value and the viability of these efforts from a financial standpoint, considering the high expenses involved in satisfying stakeholder demands. In order to get around the endogeneity issue, we incorporate the lag-dependent variable as an independent variable.

The ability of the System GMM method to handle dynamic modeling makes it preferable to other conventional approaches like Fixed and Random Effects models. Estimation flaws in the Fixed and Random Effects models make them vulnerable to omitted variable bias. This omitted variable bias can be addressed by System GMM's dynamic panel specification (Ibrahim & Rizvi, 2017).

We used the Sargan/Hansen test to test the over-identification restriction. The diagnostic findings from the AR2 and Sargan/Hansen tests support the instrument's validity. The diagnostics indicate that the lagged data are appropriate instruments. The lagged values are valid instruments in all models, according to the Sargan/Hansen test's insignificant p-value. There are no endogeneity problems with the results shown in any of the tables 7. Furthermore, by using dynamic GMM, we can account for persistence.

Table 7. The effect greenwashing on performance

Variabel	AI-GW greenwashing (AI-GW)		Databased greenwashing	
	(1)	(2)	(3)	(4)
	ROE	ROE	ROE	ROE
Greenwashing	-0.0881^{***}	-0.0742^{**}	-0.0611^{**}	-0.0575
	(-3.07)	(-2.48)	(-2.66)	(-0.50)
Leverage		0.0600		1.499^{*}
		(1.06)		(1.76)
Size		-0.0207		-0.223^{*}
		(-0.92)		(-1.79)
Liquidity		0.00224		-0.0148
		(0.11)		(-0.40)
Governance		-0.00585		-0.328^{*}
		(-0.18)		(-1.73)
L.DV	1.182^{***}	1.191^{***}	0.305^{***}	1.290^{***}
	(13.60)	(9.22)	(12.14)	(3.96)
_Cons	-0.0421^{*}	0.448	0.208^{***}	5.596^{*}
	(-1.91)	(0.75)	(10.65)	(2.01)
AR2 Stat.	1.037	1.000	-0.770	1.395
AR2 P-Val.	0.300	0.317	0.441	0.163
Hansen Stat.	17.67	12.49	11.59	2.954
Hansen P-Val.	0.281	0.407	0.479	0.815

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

Table 7 presents the estimation results in equation (1). In model 1, the measure of greenwashing uses our AI-GW without control variables. We find that greenwashing has a significant negative effect on performance (β= -0.0881, p < 0.01). In model 2, the measure of greenwashing uses our AI-GW with control variables. We find that by using AI-GW-based data, the direction of the effect of greenwashing on performance is negatively significant (β = -0.0742, p < 0.05). Likewise when using database scores in model 3 (without control variables), greenwashing still has a negative significant effect on performance (β = -0.0611, p < 0.05). The results of the hypothesis testing are consistent using both data from AI-GW and the databases.

However, in model 4, which uses a database-based greenwashing measure with control variables, the results are not significant. There are several possible causes for the differences in results, including differences in measurement and weighting between AI-GW and existing rating agencies (Berg et al., 2022).

4.1.3. Control variables

1) Leverage

High leverage levels cause financial distress (Lie, 2005) due to increased debt costs (Myers, 1977), risk shifting (Jensen & Meckling, 1976), bankruptcy costs (Warner, 1977), and asset sales. Higher leverage ratios may increase a firm's financial distress and financial constraints. Our findings show that the effect of leverage on firm performance is not significant except in model 4 where leverage has a marginal effect.

2) Size

Due to they have the resources to pursue business opportunities in sectors that require large capital investments, larger organizations can benefit from economies of scale and imperfect competition (Baumol, 1959). This connection has been confirmed by other studies (Hall & Weiss, 1967; Serrasqueiro & Maçãs Nunes, 2008). To manage the impact of that size, we substituted the natural logarithm of total assets (SIZE) for firm size. The results of this research indicate that using AI-GW and database data shows that performance is unaffected by the size of the company except in model 4 where size has a marginal effect.

2) Liquidity

A liquid company is a company with easy access to cash, meaning that the company can manage liquid assets efficiently. Efficient asset management can reduce financial constraints and increase the company's financial flexibility. By using AI data and database, the results of this study show that company liquidity has no effect on performance.

3) Governance

We added the number of board members as a control variable. The results show that the number of board members has no effect on performance, using both data from AI-GW and the database, except in model 4 where governance has a marginal effect.

4.1.4. Robustness test

This study adopts alternative measures of the dependent variables to undertake further robustness tests. TobinQ is used as an alternative measure of market-based performance. In

Table 8 the results in model 1 show that when using TobinQ as the dependent variable, in the AI-GW data, greenwashing has a significant negative effect on performance (β = -0.0292, p < 0.01) and so it is in model 2 (β = -0.0376, p < 0.01). Likewise, using database scores (model 4), greenwashing still has a negative effect on performance (β = -0.117, p < 0.01).

Table 8. Robustness test

Variabel		AI-GW greenwashing (AI-GW)		Databased greenwashing
	(1) TobinQ	(2) TobinQ	(3) TobinQ	(4) TobinQ
Greenwashing	-0.0292***	-0.0376***	-0.00667	-0.117***
	(-7.30)	(-2.79)	(-0.43)	(-3.17)
Leverage		0.126**		-0.250*
		(2.34)		(-1.85)
Size		-0.0452***		-0.102***
		(-3.52)		(-3.72)
Liquidity		-0.00171		-0.0970***
		(-0.22)		(-5.62)
Board Size		-0.0114		0.00835
		(-0.29)		(0.11)
Lag MTB	0.863***	0.840***	0.845***	0.412***
	(90.88)	(26.04)	(223.85)	(35.68)
_Cons	0.0123***	1.116***	0.0272***	2.891***
	(4.55)	(3.53)	(5.68)	(4.35)
AR2 Stat.	1.053	1.008	-0.701	-0.757
AR2 P-Val.	0.292	0.313	0.483	0.449
Hansen Stat.	11.41	6.253	22.10	21.06
Hansen P-Val.	1.053	1.008	0.181	0.0595

In this table, In Model (1), our main independent variable is our AI-GW-based greenwashing without any control variables. In Model (2), our main independent variable is our AI-GW based greenwashing with control variables. In Model (3), our main independent variable is database-based greenwashing without any control variables. In Model (4), our main independent variable is database-based greenwashing with control variables.

The test results show that greenwashing reduces market-based performance. This is in line with Xu et al. (2025) conclusions that greenwashing has a detrimental impact on the market. Table 8 shows that the robustness test's regression results resemble the earlier primary findings in Table 7. With the alternative measure, the results are therefore robust.

Conclusion

5.1. Conclusion

The primary goal of the study is to evaluate the effectiveness of AI-based greenwashing detection by examining whether there is a difference between greenwashing scores using database-based data and AI-GW-based data? And does using data from AI-GW and databases produce the same results regarding whether greenwashing affects performance?. The findings indicate that there is no difference in greenwashing scores based on our AI-GW and data that is from databases.

Using natural language processing, we assign greenwashing scores to Indonesian listed companies that have ESG scores and ESC disclosure data from Bloomberg and Thomson Reuters. We show that the AI-GW score is positively correlated with the Bloomberg and Thomson Reuters scores.

In this study, we clarify that greenwashing has a negative effect on financial performance, consistent across AI-GW derived scores and database-derived ones. This is consistent with the findings of Birindelli et al. (2024), Neumann, (2021), and Walker & Wan (2012) that used a greenwashing strategy cause performed worse. Symbolic action without being followed by substantive action may represent perceived loss from stakeholders.

The results of this study confirm the validity of the AI-based greenwashing score we developed. Our study will contribute to future research aimed at clarifying the relationship between greenwashing and corporate performance. Future research could also increase the coverage of research data, especially in countries with low Bloomberg and Thomson Reuters data coverage.

5.2. Implications

5.2.1. Theoretical implications

This study provides the same empirical results from using databases and AI-GW. The validity of AI-GW-based data provides a solution to the lack of data coverage from Thomson

Reuters and Bloomberg. Chen et al. (2024) also stated that the low coverage of ESG score data from Thomson Reuters and Bloomberg for companies in Japan was only 11%. Meanwhile, for data in Indonesia in 2017-2022, the coverage of ESG scores from Thomson Reuters and Bloomberg was only 7%. This finding contributes to a comprehensive measurement of greenwashing. The use of AI technology can improve the quality of decision-making, thus potentially reducing disagreements between rating agencies. This study also contributes to the debate on the effect of greenwashing on performance. By providing an analysis using AI-based data and databases produces consistent results that greenwashing has a negative effect on company performance.

5.2.2. Policy implications

Incomplete regulatory systems and weak law enforcement in developing countries make it difficult to assess and evaluate corporate environmental performance (Doh et al., 2010; Wei et al., 2017). Moreover, most external stakeholders seek corporate sustainability information through termination reports and websites (S. Du et al., 2007; McWilliams & Siegel, 2000), while interpreting information in reports requires complex professional knowledge (Carlson et al., 1993). The existence of information asymmetry, low quality of information, and stakeholders' limitations in processing information make it impossible for stakeholders to identify and punish greenwashers (W. Li et al., 2022). Therefore, the greenwashing detection model (AI-GW) whose validity has been tested in this study is expected to help regulators and banks in detecting companies suspected of greenwashing. For regulators, with AI-GW being able to rank companies based on the gap between performance and environmental communication, the ratings given will improve the quality of stakeholder decision-making.

For banks, our AI-GW is useful for imposing credit restrictions on companies that engage in symbolic communication without substantive action or engage in greenwashing. Credit constraints can encourage investment in corporate innovation projects that promote sustainability (Hottenrott & Peters, 2012). Credit constraints can impact a company's ability to innovate greenly (Gong et al., 2020). Strict environmental regulations and credit constraints will force companies to implement green innovation (Berrone et al., 2013).

5.3. Further Research

Apart from the contribution it makes, this research also has weaknesses: First, incomplete data from Thomson Reuters and Bloomberg is the reason for the lack of research data. Second, the AI-GW flaw requires a lengthy program execution time. Detection for one company takes about an hour; therefore, in the future, the application must be improved by using the Application Programming Interface (API) to support the application's speed. This study also highlights the need for more robust models to accurately measure the impact of greenwashing in different contexts. Apart from that, future research could compare the robustness of AI-GW with the scores of other rating agencies.

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Appendix

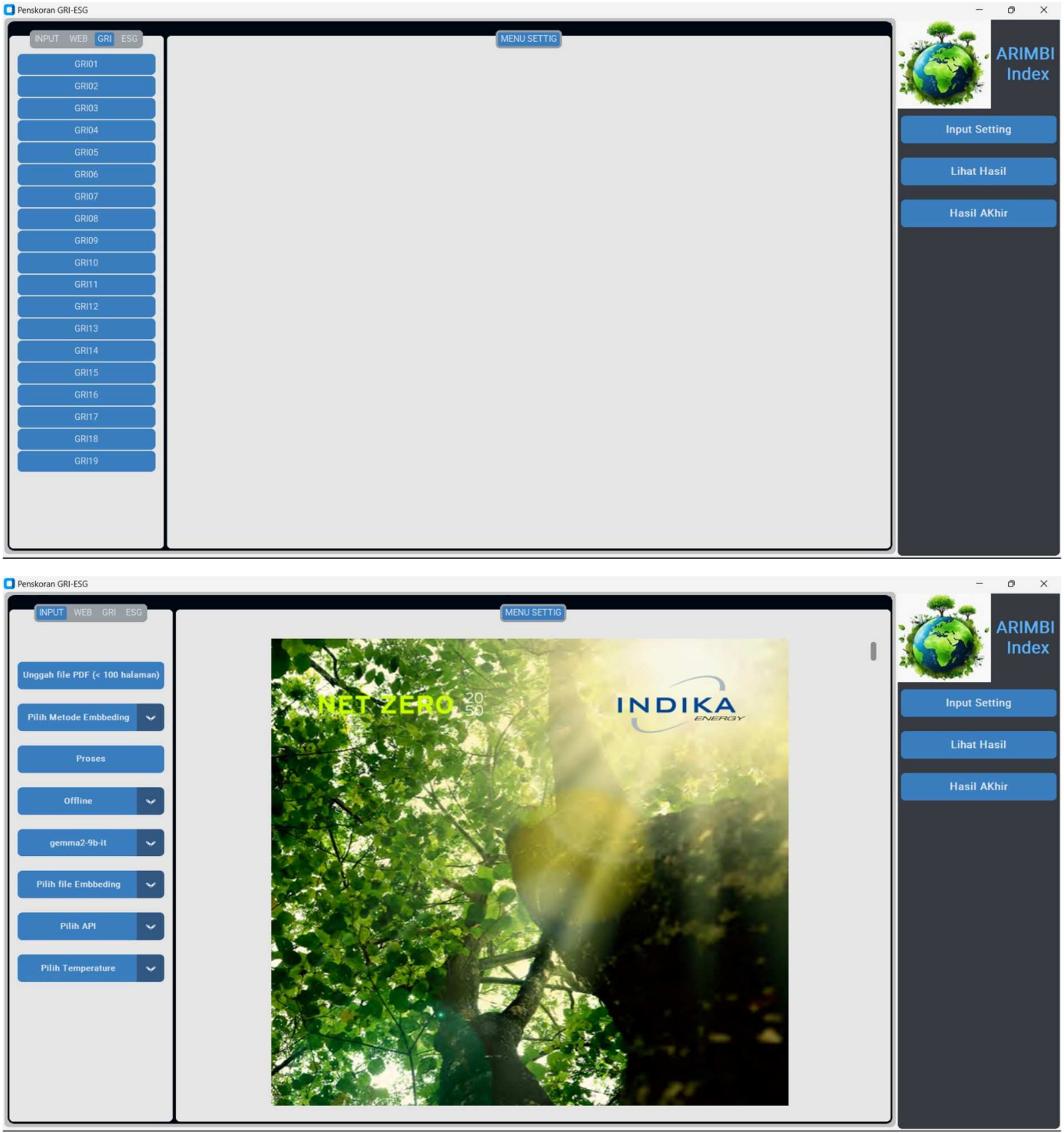

Figure A1. AI GW Application Display