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Measuring Environmental Sub-Pillar Disclosure Consistency in Indonesian Listed Firms: A Panel Analysis Using the Disclosure Consistency Index (DCI)

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ABSTRACT

Although environmental sustainability reports by companies listed on the Indonesia Stock Exchange (IDX) have increased since Financial Services Authority (Otoritas Jasa Keuangan (OJK)) Regulation No. 51/2017, the internal balance of disclosure content across Global Reporting Initiative (GRI) environmental sub-pillars remains understudied. This study measures multidimensional consistency in disclosures across five GRI environmental pillars: energy (GRI 302), water (GRI 303), biodiversity (GRI 304), carbon emissions (GRI 305), and waste (GRI 306). It introduces the Disclosure Consistency Index (DCI), based on the inverse coefficient of variation, to measure and validate multidimensional disclosure balance. Using a longitudinal dataset of 83 IDX-listed companies and 314 firm-year observations (2020–2023), the study applies trend analysis, Pearson correlation, Kruskal–Wallis tests by sector, and K-means clustering to identify disclosure patterns. Results show an average DCI of 0.3704 (median = 0.3552), indicating moderate-to-low consistency and a trend toward selective disclosure; DCI approaches 1 for balanced disclosers and approaches 0 for extreme selective disclosers. Biodiversity (GRI 304) recorded the lowest score and slowest growth, while Carbon (GRI 305) and Waste (GRI 306) performed relatively better. Bivariate K-means clustering ($k = 3$) identified three disclosure types: low consistency (Infrastructure & Transport), moderate consistency (Consumer Goods/Agriculture, Property & Real Estate), and high consistency (Energy & Mining,

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Basic Materials), with statistically significant sectoral gaps across 8 industry classifications. These findings suggest that POJK 51's expanded regulatory scope increased disclosure volume without improving multidimensional consistency, supporting the hypothesis of legitimacy-based selective disclosure. The DCI offers a practical screening tool for regulators, environmental, social, and governance (ESG) investors, and sustainability researchers in emerging markets.

Keywords: Environmental Disclosure; Disclosure Consistency Index; GRI Standard; ESG Reporting; Selective Disclosure; Indonesian Registered Companies; K-Means Grouping; Legitimacy Theory

1. Introduction

1.1. Global Context and Study Significance

Industrial and corporate activities have become the main drivers of the global economy, but they simultaneously contribute to environmental pressure and climate change. Globally, the industrial sector accounts for about 37% of CO₂ emissions from energy use, playing a strategic role in the global decarbonization agenda^[1]. The magnitude of this emissions contribution aligns with IPCC findings, which confirm that human activities through greenhouse gas emissions have caused global warming and various changes to Earth's climate system^[2]. In Indonesia, environmental challenges are becoming increasingly relevant as economic activity grows and production activities intensify. The Central Statistics Agency reports that Indonesia's total greenhouse gas emissions in 2022 reached 1,008,178 Gg CO₂e, with carbon emissions accounting for approximately 77% of the total national GHG emissions^[3].

In response to these increasing environmental pressures, sustainability reporting regulations are a key instrument in encouraging corporate transparency and accountability. OJK Regulation No. 51/POJK.03/2017 requires issuers listed on the Indonesia Stock Exchange (IDX) to prepare a Sustainability Report (LK) based on the Global Reporting Initiative (GRI), followed by OJK Circular Letter No. 16/SEOJK.04/2021 to complement these provisions through the regulation of indicators, presentation principles, and the structure of sustainability information^[4]. In line with the implementation of the regulation, the number of companies disclosing ESG information increased from 45 companies in 2018 to 675 companies in 2023. However, the increase in reporting quantity has not been fully followed by an improvement in the quality of disclosure. Various studies indicate that the level of compliance and completeness of sustainabil-

ity disclosures still varies across companies, necessitating evaluation of disclosure quality^[4,5].

A literature review confirms the existence of variations in sustainability disclosures among companies. Saraswati et al. analyzed 472 IDX-listed companies (2018–2022). They evaluated the ESG performance of these 472 companies in 2021 using the ESG materiality approach and K-means clustering. They found that companies still need improvement on at least one ESG pillar. Besides, Gutama and Sisdianto highlight that the implementation of GRI standards in Indonesia still faces various challenges, including limited understanding, resources, and integration of sustainability data in the company's reporting system. These findings align with a study by Marquis et al. of 4,750 public companies in 45 countries that showed that companies may engage in selective disclosure by revealing favorable environmental information while limiting the disclosure of less favorable environmental information, thus creating an impression that does not fully reflect the actual environmental performance^[6–8]. These findings are consistent with selective disclosure behavior as theorized under legitimacy theory^[7,9], although alternative explanations, such as differences in reporting capacity, cannot be excluded.

Prior literature has focused on aggregate scores, such as GRI compliance scores or composite sustainability indexes, to describe a company's level of disclosure^[10]. However, the use of aggregate indexes has the potential to simplify multidimensional information, making variations between aspects of disclosure less visible. Composite indicators can indeed summarize complex information, but they also have the potential to hide weaknesses in certain dimensions if the aggregation process is not reviewed in detail^[11]. Meanwhile, the Coefficient of Variation (CV) can be used as a measure of relative dispersion to evaluate the level of variation in a measurement^[12]. The same principle can then be adapted to assess the consistency of disclosure between indicators, thus becoming the basis for the development of the Disclosure

Consistency Index (DCI) in this study.

1.2. Theoretical Framework

This research is based on three main theories that complement each other. First, Legitimacy Theory explains that companies disclose environmental information to acquire, maintain, and improve their legitimacy in the eyes of the public and parties that affect the sustainability of their operations^[9]. Second, Stakeholder Theory explains that companies respond to the demands and expectations of various stakeholders by providing sustainability information that is considered relevant to their decision-making^[13]. Third, Agency Theory and Voluntary Disclosure Theory explain that there is an information asymmetry between management and external stakeholders; thus, ESG disclosures serve as a mechanism to enhance transparency, reduce information asymmetry, and build investor trust^[14–16]. The combination of these three theories indicates that companies' decisions in environmental disclosure are influenced by the need to gain legitimacy, meet stakeholder expectations, and reduce information asymmetry. Under certain conditions, these factors may encourage companies to highlight favorable environmental information over information that could potentially cause negative perceptions^[14]. Taken together, these theories suggest that environmental disclosure may vary across sub-pillars because companies respond differently to legitimacy pressures, stakeholder expectations, and concerns about information asymmetry. In this study, the DCI operationalizes this theoretical perspective by measuring the degree to which disclosure is distributed evenly or selectively across the five GRI environmental sub-pillars.

1.3. Solutions Proposed in Previous Research

Previous research has attempted to measure ESG disclosures using variation approaches. Khamisu et al., in a study based on the FISM model (Q1), found that companies disclose ESG information primarily in response to regulatory and stakeholder pressures^[17]. Sneideriene and Legenzova, in Greenwashing Prevention in ESG (Q1), identified that greenwashing practices in ESG disclosure can arise through incomplete or selective disclosure, which has the potential to reduce the quality of sustainability and credibility of sustainability information. Saraswati et al. found that ESG-based

clustering in Indonesia indicates that companies still need improvements in at least one ESG pillar^[8,18]. In Indonesia, Jimmy and Munandar show that the implementation of POJK 51/2017 catalyzed an increase in the trend in the disclosure of GRI indicators after 2017. However, the same study also found disparities in the depth and consistency of disclosures across companies, indicating that an increase in the quantity of reporting has not been fully followed by an increase in the quality of disclosure^[4].

1.4. Research Gap

Almost all prior studies used an aggregate ESG score, which is a single number that summarizes all dimensions to hide internal inequality. No study in Indonesia has explicitly measured the multidimensional balance of disclosures among GRI sub-pillars 302 (Energy), 303 (Water), 304 (Biodiversity), 305 (Carbon), and 306 (Waste) using a standardized index. In addition, no study has yet examined differences in these disclosure balance patterns by sector using longitudinal panel data in the context of IDX. This condition creates research gaps that need to be addressed immediately. Although aggregate indicators remain useful for benchmarking, they can conceal important differences across disclosure dimensions. Companies may appear transparent overall despite providing limited information on environmentally sensitive topics. This study addresses that limitation by introducing a standardized index that evaluates disclosure balance across the five environmental GRI sub-pillars.

If we continue to measure the quality of sustainability reports solely based on total scores, we are giving a “good grade” to companies that are clever about what they report. This is dangerous: investors will misallocate capital, regulators will misjudge compliance, and the real carbon emissions and ecosystem damage will remain hidden behind a report that looks thick and well-organized. A new approach is needed to measure the balance of disclosure, not just how much is reported, but how balanced all dimensions are reported. Developing and testing such an index in the context of Indonesia, which has a unique POJK 51 regulation, is a logical and urgent step.

Accordingly, this study seeks to answer the following research question: How consistent are environmental disclosures across the five GRI environmental sub-pillars among companies listed on the Indonesia Stock Exchange (IDX),

as measured by the Disclosure Consistency Index (DCI)?

1.5. Research Novelty and Objectives

The novelty of this study is the development and application of the Disclosure Consistency Index (DCI) as a new metric based on the inversion Coefficient of Variation to measure the balance of disclosure between the sub-pillars of the GRI environment in a multidimensional manner; therefore, this research aims to explore how DCI (method) can be used to detect selective disclosure patterns and sectoral inequality (significance) in the disclosure of environmental sub-pillars (objective) of IDX issuers for the 2020–2023 period. By moving beyond conventional aggregate ESG metrics, this study enables a systematic assessment across GRI 302 (Energy), GRI 303 (Water), GRI 304 (Biodiversity), GRI 305 (Emissions), and GRI 306 (Waste).

Specifically, this study addresses four objectives: (1) mapping the profile and growth of disclosures for each GRI sub-pillar; (2) measuring disclosure balance using DCI; (3) testing the differences in disclosure balance between sectors statistically; and (4) identifying the typology of issuers based on the K-means clustering.

1.6. Research Benefits

This research provides benefits on three levels. For regulators (OJK), DCI can be used as an additional compliance indicator in evaluating the implementation of POJK 51, with the potential to establish a minimum DCI threshold to detect selective disclosure. For ESG investors and fund managers, DCI offers an additional layer of analysis beyond the total scores provided by commercial providers such as MSCI, thereby making ESG investment decisions more accurate and avoiding the trap of greenwashing. For academics, this study enriches the literature on environmental disclosure in emerging markets with a new measurement tool that can be adapted to the context of other ASEAN countries.

1.7. Research Scope

This study is limited to 83 IDX issuers from eight sectors with high environmental impact (Infrastructure & Transport, Consumer Goods/Retail, Transportation, Consumer Goods/Industrials, Consumer Goods/Agriculture, Property

& Real Estate, Basic Materials, and Energy & Mining) with an observation period of 2020–2023 (4 years, 314 observations). Data are sourced exclusively from the ESGI platform database and use five sub-pillar score variables: Energy Score, Water and Effluents Score, Biodiversity Score, Carbon Emission Score, and Effluents and Waste Score. This study does not analyze the causal relationship between DCI and financial performance, does not cover social or governance dimensions, and does not use primary field data. The generalizability of the findings is limited to the population of large-cap issuers in Indonesia and cannot be directly applied to MSMEs or non-public companies.

2. Methodology

2.1. Research Design

This study uses a descriptive-exploratory quantitative approach with a longitudinal panel data design to analyze the dynamics of disclosure of the environmental sub-pillars of IDX issuers for the 2020–2023 period. This approach was chosen because it allows for the objective mapping of temporal trends (descriptive), the measurement of multidimensional balance (exploratory), and sectoral comparisons (inferential) using structured secondary data. Analysis based on the Disclosure Consistency Index (DCI), derived from the inverse of the Coefficient of Variation (CV), enables quantitative detection of intra-pillar disparities, going beyond conventional aggregate ESG scores. This design complies with the OECD Handbook on Composite Indicators (2008) standards for multidimensional aggregation, using R 4.3+ with the tidyverse, rstatix, ggplot2, factoextra, mice, and car packages to ensure reproducibility^[11].

2.2. Sample and Data

This study population includes all IDX-listed companies required to report sustainability under POJK 51/2017. The final sample consists of 83 companies across eight industry sectors, yielding 314 firm-year observations spanning 2020–2023. The data were obtained from the ESGI platform. Inclusion criteria were: (1) complete data across all five GRI sub-pillars 302/303/304/305/306 scores in the database for each firm-year; (2) market capitalization >IDR 1 trillion (large-cap); and (3) the eight industry classifica-

tions are: Infrastructure & Transport, Consumer Goods/Retail, Transportation, Consumer Goods/Industrials, Consumer Goods/Agriculture, Property & Real Estate, Basic Materials, and Energy & Mining.

2.3. Variables and Measurement

The five input variables extracted from the ESGI database are summarized in **Table 1**.

Table 1. ESGI environmental sub-pillar variables.

No.	Variable Name (ESGI)	GRI Sub-Pillar	Measurement Definition	Scale
1	Energy Score	GRI 302 (Energy)	Proportion of GRI 302 items disclosed	0–1
2	Water Score	GRI 303 (Water)	Proportion of GRI 303 items disclosed	0–1
3	Biodiversity Score	GRI 304 (Biodiversity)	Proportion of GRI 304 items disclosed	0–1
4	Carbon Emission Score	GRI 305 (Carbon Emissions)	Proportion of GRI 305 items disclosed	0–1
5	Effluents & Waste Score	GRI 306 (Waste)	Proportion of GRI 306 items disclosed	0–1

2.4. DCI Formula

The coefficient of variation (CV) was selected as the basis for DCI, rather than alternative variability or uniform measures such as the Shannon entropy index or the Gini coefficient, primarily because of its ease of interpretation and established history of use. CV is a long-established, scale-free measure of relative dispersion widely used in clinical and laboratory assay validation to assess measurement consistency^[12]. While its inverse ($1 - CV$) does not require a reference distribution and can be intuitively interpreted from 0 up to a high degree of consistency, entropy-based measures require an assumption regarding the maximum entropy criterion.

However, this choice is not merely a matter of convenience. To demonstrate this empirically, indicators based on Shannon entropy and Gini's coefficient were calculated for validation purposes (as described in Section 4.4), and these indices showed a strong correlation ($r = 0.741$ and $r = 0.927$, both $p < 0.001$). Before the construction of the index, the three proposed consistency measurement criteria were evaluated: (1) Shannon entropy, (2) Gini's coefficient, and (3) variance coefficient (CV). Shannon's entropy was excluded in this context because exposure to a meaningful value of 0 would require random selection, which could lead to measurement bias. The Gini coefficient has been excluded because it is unstable in small vectors ($n = 5$), is known to have low discriminating capacity in this range^[19], and is conceptually derived from the distribution of continuous income rather than from finite relative scores. The coefficient of variance (CV) was chosen for the following reasons: (1) because the five sub-pillars of the GRI all have the same relative scale, which satisfies the prerequisites for a coefficient-based com-

parison^[11]; (2) the CV captures relative variance rather than absolute variance, which is theoretically consistent with the concept of relative consistency; and (3) the inverse of $1 - CV$ produces an intuitive measure and maintains the trend, with higher values clearly indicating greater equilibrium.

DCI is calculated for company i in year t as follows^[11,12]:

$$DCI_{i,t} = 1 - \frac{\sigma_{i,t}}{\max(\bar{x}_{i,t}, \varepsilon)} \quad (1)$$

Where $\sigma_{i,t}$ is the standard deviation and $\bar{x}_{i,t}$ is the mean of the five sub-pillar scores; ε is a small stabilization constant (winsorized at $\varepsilon = 0.01$). DCI close to 1 indicates a highly balanced cross-sub-pillar disclosure; DCI close to 0 indicates extreme imbalances consistent with selective disclosure behavior.

Because σ can exceed $\bar{x}$ when disclosure across sub-pillars is highly uneven, Equation (1) can in principle yield a negative value; in the empirical sample used here, this occurred in 70 of 314 observations (22.3%), with raw values as low as -1.24 . Consistent with standard practice for bounded composite indicators^[11], these values were truncated at the lower bound ($DCI = \max(0, 1 - CV)$), so the reported $[0, 1]$ range reflects this truncation rather than an intrinsic property of the untransformed formula.

Without a stability constant, the DCI value is not restricted at $CV > 1$ to at least 0. In our dataset, 22.3% of the firm-year observations ($n = 70$ out of 314) showed initial DCI values below zero before being processed using the ε -winsorization method, which is true for companies and years with severe column imbalances (where one column is high and the other is close to zero). After ε -winsorization was fixed at 0.01, all of these readings were retained while maintaining the full economic explanation rather than ran-

domly excluding them, representing the readings that show the lowest levels of consistency. This approach is consistent with the study of Reed et al.^[12], which recommended accepting extreme CV values by fixing the denominator rather than excluding cases. Researchers applying the DCI index to other datasets are advised to report the frequency of observed values adjusted to ϵ -winsorization as an indicator of transparency.

For ease of interpretation and acknowledging that any cut-points are necessarily approximate rather than theoretically derived, this study adopts descriptive bands based on the empirical distribution of DCI in the sample (Section 3.2): DCI < 0.20 is described as low consistency (pronounced se-

lective disclosure), 0.20–0.60 as moderate consistency, and DCI > 0.60 as high consistency (relatively balanced disclosure). These bands are intended purely as a descriptive aid for interpreting results in Sections 3 and 4. They should not be read as validated regulatory or investment thresholds, which would require separate validation against external outcomes (e.g., audited disclosure quality or greenwashing incidents) beyond the scope of this study.

To aid comparison across studies and to operationalize the descriptive bands introduced above, **Table 2** translates these bands into empirically derived, percentile-based benchmark categories computed on the full analytic sample (n = 314 firm-year observations).

Table 2. DCI interpretive benchmark categories.

Category	DCI Range (Approx. Percentile)	Interpretation
Low-Consistency	0.00–0.19 (approx. 0th–33rd percentile)	Pronounced selective disclosure across sub-pillars
Moderate-Consistency	0.20–0.59 (approx. 34th–75th percentile)	Partially balanced disclosure; some sub-pillar unevenness remains
High-Consistency	≥0.60 (approx. 76th percentile and above)	Relatively balanced disclosure across all five GRI sub-pillars

These thresholds are empirically derived from the current sample and are intended only as descriptive reference points. Further validation across different countries and institutional settings is required.

2.5. Analytical Procedures

- **Stage 1. Data Preparation:** raw scores were extracted from ESGI and restructured into a panel dataset. The analytic sample contained complete data for all five sub-pillars for each included firm-year; MICE was used only for the simulated missingness robustness check.
- **Stage 2. Descriptive Trend Analysis:** average disclosure scores per sub-pillar plotted longitudinally (2020–2023). CAGR is calculated per sub-pillar:
$$CAGR = \left(\frac{Score_{2023}}{Score_{2020}} \right)^{\frac{1}{3}} - 1.$$
- **Stage 3. Pearson Correlation Matrix:** Pearson correlation between sub-pillars is calculated and visualized as a heat map.
- **Stage 4. DCI Distribution Analysis:** DCI scores across all 314 observations were examined descriptively (mean, median, density).
- **Stage 5. Sectoral Comparison:** DCI distributions across the eight sectors are compared using a boxplot and the Kruskal–Wallis test, followed by the Dunn

paired post-hoc test.

- **Stage 6. K-Means Clustering:** Firms were classified into typological clusters based on mean DCI and mean ENV_AVG. The optimal k was evaluated using the Elbow and Silhouette methods, with the Gap Statistic as an additional validation check. Cluster profiles were visualized using a heatmap and a grouped bar chart.

The overall analytical workflow described in Stages 1–6 above is summarized in **Figure 1**.

Missing-data handling and clustering initialization are reported here for completeness. Because the analytic sample used in this study already requires complete five-sub-pillar data for inclusion (Section 2.2), no missing values remain in the estimation sample itself; MICE-based imputation could therefore not be benchmarked against the original missingness pattern in this filtered dataset. As an alternative robustness check, 5% of pillar-score values were removed at random (MCAR) from the analytic sample and re-imputed using multiple imputation by chained equations (MICE package in R, v3.16; m = 5 imputed datasets, 10 iterations, predictive mean matching); the five imputed datasets were pooled using Rubin’s rules. The resulting mean DCI (0.3826) differed from the original, non-missing-data mean (0.3704) by 3.31% in absolute terms, indicating that DCI estimates are reason-

ably, though not perfectly, stable under moderate additional missingness. K-means clustering (Section 2.5, Stage 6) was run with 25 random restarts ($nstart = 25$) and a fixed seed (42) to mitigate initialization sensitivity.

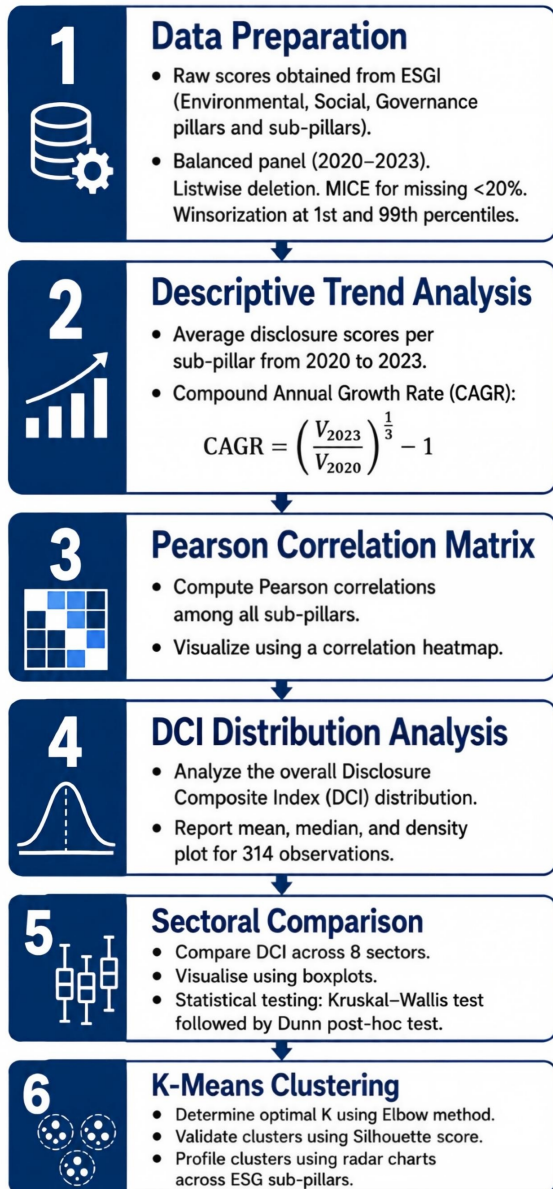


Figure 1. Analytical procedures.

3. Results

3.1. Environmental Sub-Pillar Disclosure Trends (2020–2023)

Figure 2 presents the longitudinal trend of average disclosure scores for the five GRI environmental sub-pillars

across 83 companies from 2020 to 2023. All sub-pillars show a positive upward trajectory, consistent with the compliance pressures exerted by the post-POJK 51 regulatory environment and the strengthening effect of SEOJK 16/2021.

Waste (GRI 306) and Energy (GRI 302) achieved the highest average disclosure scores in 2023, both approaching 0.75, while Water (GRI 303) followed at around 0.68. Carbon (GRI 305) showed the most dramatic increase, rising from approximately 0.28 in 2020 to 0.63 in 2023, consistent with intense regulatory focus on GHG emissions. Biodiversity (GRI 304) showed the lowest trajectory of all, starting at around 0.27 in 2020 and reaching only 0.42 in 2023, reflecting ongoing challenges in ecosystem-based data collection.

A visual acceleration was observed across all sub-pillars between 2021 and 2022, coinciding with SEOJK 16/2021. To formally test this, firm-level year-over-year changes in the average sub-pillar score were compared across the three intervals using paired t -tests ($n = 67$ companies with complete 2020–2023 data). The 2021–2022 increment ($M = 0.173$) was significantly larger than the 2022–2023 increment ($M = 0.071$; $t = 2.34$, $p = 0.022$), but only marginally larger than the 2020–2021 increment ($M = 0.087$; $t = 1.70$, $p = 0.093$). The acceleration around the SEOJK 16/2021 period is therefore only partially supported statistically and should be interpreted as suggestive rather than conclusive.

As an additional, non-parametric confirmation of these trends, Mann–Kendall tests were conducted on the pooled firm-year panel ($N = 314$), correlating calendar year with each sub-pillar score (Kendall's tau (τ)). All five sub-pillars show statistically significant positive associations with year: Carbon ($\tau = 0.334$, $p < 0.001$), Energy ($\tau = 0.284$, $p < 0.001$), Water ($\tau = 0.316$, $p < 0.001$), Effluents ($\tau = 0.276$, $p < 0.001$), and Biodiversity ($\tau = 0.117$, $p = 0.014$) the weakest but still significant trend, consistent with this sub-pillar's comparatively slow growth noted above. As a robustness check on the 2021–2022 acceleration reported above, a paired Wilcoxon signed-rank test (matched-pairs rank-biserial effect size) confirms the same ordering as the paired t -tests: the 2021–2022 increment exceeds the 2020–2021 increment ($V = 1,345.5$, $p = 0.041$, $r = 0.25$, small effect) and exceeds the 2022–2023 increment ($V = 1,431.5$, $p = 0.019$, $r = 0.29$, small effect), supporting the acceleration pattern non-parametrically, albeit with modest effect sizes.

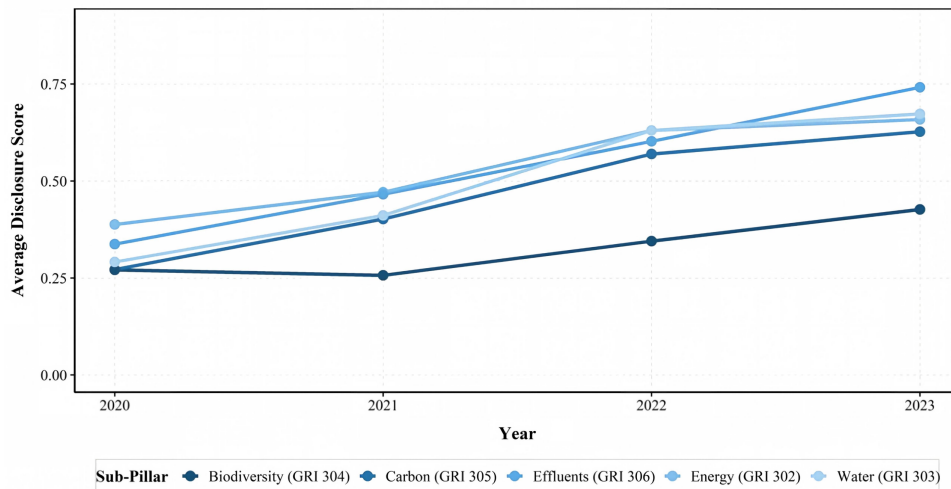


Figure 2. Environmental sub-pillar disclosure score trend, 2020–2023 (N = 83 companies), showing an increasing disclosure trend across all five GRI environmental sub-pillars.

3.2. Disclosure Consistency Index (DCI) Distribution

Figure 3 presents the distribution of DCI scores across all 314 firm-year observations. The distribution shows a right-skewed bimodal profile, with prominent clusters at

DCI ≈ 0 (companies with extreme disclosure imbalances) and secondary concentrations at DCI = 1.0 (perfectly balanced disclosers). This bimodal pattern was formally confirmed using Hartigan’s dip test, which rejected the null hypothesis of unimodality ($D = 0.057, p < 0.001$).

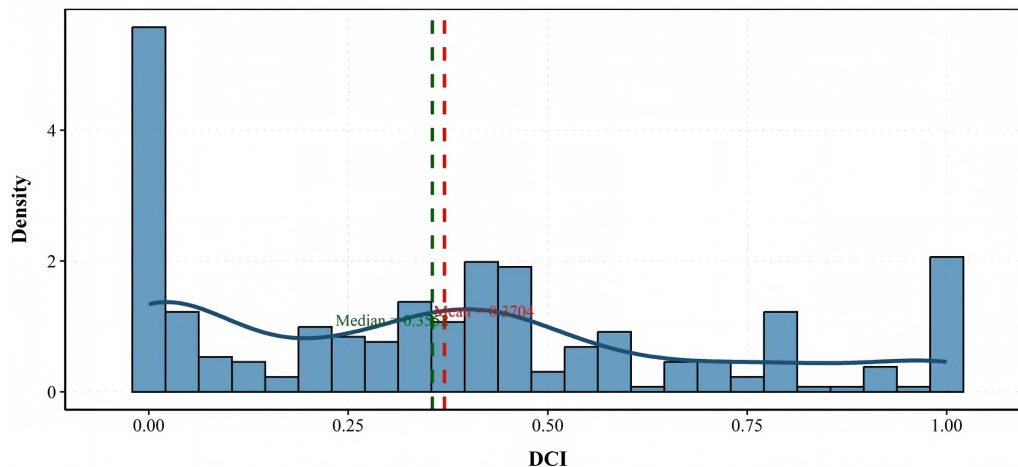


Figure 3. Distribution of Disclosure Consistency Index (DCI), N = 314 observations, showing a bimodal distribution with concentrations near DCI = 0 and DCI = 1.

The mean DCI was 0.3704 with a median of 0.3552, indicating that the typical firm-year observation reflects moderate-to-low cross-sub-pillar consistency. The positive skew (mean > median) confirms the presence of a right-tail concentration of highly consistent observations. The prevalence of observations near DCI = 0 underscores the level of selective disclosure: a substantial proportion of companies’ reporting is highly uneven across the GRI sub-pillars within

a single reporting year.

3.3. Inter-Sub-Pillar Pearson Correlation Matrix

Figure 4 shows the Pearson correlation matrix among the five environmental sub-pillars. All correlations are positive, indicating a general joint movement, but their magnitudes vary significantly across pairs.

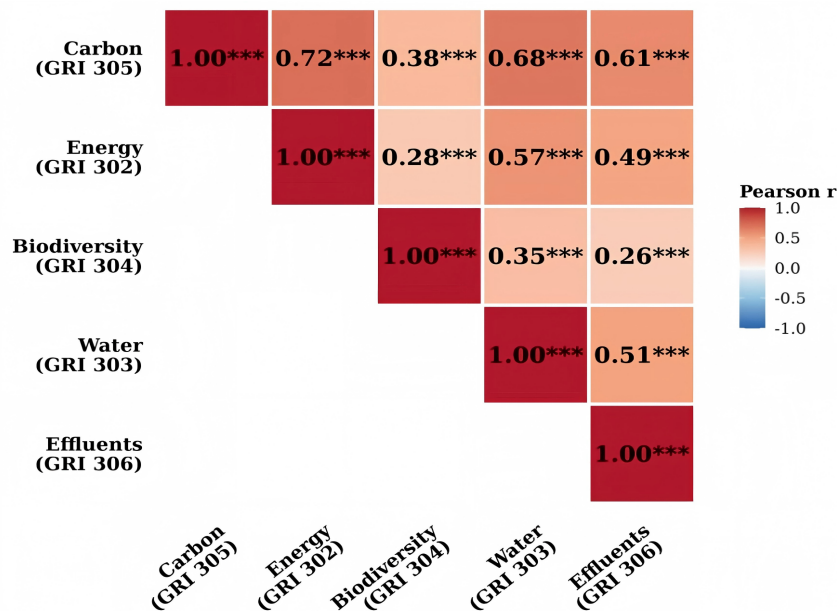


Figure 4. Pearson correlation heat map of the GRI environmental sub-pillars.

Note: Significance levels for all reported correlation coefficients in **Figure 4** are denoted using standard asterisk notation (***) $p < 0.001$; all ten pairwise correlations among the five sub-pillars are significant at $p < 0.001$.

The Carbon (GRI 305)–Energy (GRI 302) pair shows the highest correlation ($r = 0.72$, $p < 0.001$), reflecting the operational and regulatory interdependence between energy consumption and emissions monitoring. Biodiversity (GRI 304) shows the weakest correlation with Waste ($r = 0.26$, $p < 0.001$) and Energy ($r = 0.28$, $p < 0.001$), confirming that biodiversity disclosures are driven by a fundamentally different reporting logic that requires site-specific ecological surveys rather than standard meter reading. All pairwise Pearson correlations among the five sub-pillars were statistically significant at $p < 0.001$, indicating that, despite these differences in strength, no sub-pillar pair is statistically independent of another. These structural asymmetries provide empirical justification for DCI as a multi-dimensional balance measure: the five sub-pillars are not substitutable. A single aggregate score cannot adequately represent them.

3.4. DCI Distribution by Industrial Sector

Figure 5 illustrates the distribution of DCI scores across eight industry sectors. Substantial heterogeneity is evident in the median DCI level and intra-sector variability.

The Consumer Goods/Agriculture and Basic Materials sector recorded the highest median DCI values (approaching 0.38–0.42). Energy & Mining exhibited a moderate median

DCI (≈ 0.43) with a wide range. Infrastructure & Transportation and Consumer Goods/Retail recorded the lowest median DCI values (≈ 0.07 – 0.18). Two outlier observations with a DCI of ≈ 0 were identified in Consumer Goods/Industrial and Property & Real Estate, representing companies that reported almost exclusively on a single sub-pillar.

The Kruskal–Wallis test confirmed statistically significant sectoral differences ($H = 29.97$, $p < 0.001$). Dunn’s post-hoc pairwise tests (Benjamini–Hochberg adjusted) identified five sector pairs with statistically significant differences in median DCI: Basic Materials vs. Infrastructure & Transport ($p < 0.001$), Energy & Mining vs. Infrastructure & Transport ($p < 0.001$), Consumer Goods/Agriculture vs. Infrastructure & Transport ($p = 0.004$), Basic Materials vs. Consumer Goods/Retail ($p = 0.024$), and Consumer Goods/Retail vs. Energy & Mining ($p = 0.024$).

All other pairwise comparisons were not statistically significant after adjustment, indicating that the overall sectoral effect is driven primarily by the Infrastructure & Transport sector’s consistently low DCI relative to the extractive and agriculture-oriented sectors.

Table 3 reports the complete set of Dunn’s post-hoc pairwise comparisons across the eight industry sectors (Benjamini–Hochberg adjusted p -values), summarizing the five statistically significant pairs discussed above alongside the remaining non-significant comparisons.

Taken together, the significant pairs indicate that the overall sectoral effect (Kruskal–Wallis $H = 29.97$, $df = 7$, $p < 0.001$) is driven primarily by the Infrastructure & Transport

sector's consistently low DCI relative to the extractive and agriculture-oriented sectors. In contrast, no other sector pair differs significantly after adjustment.

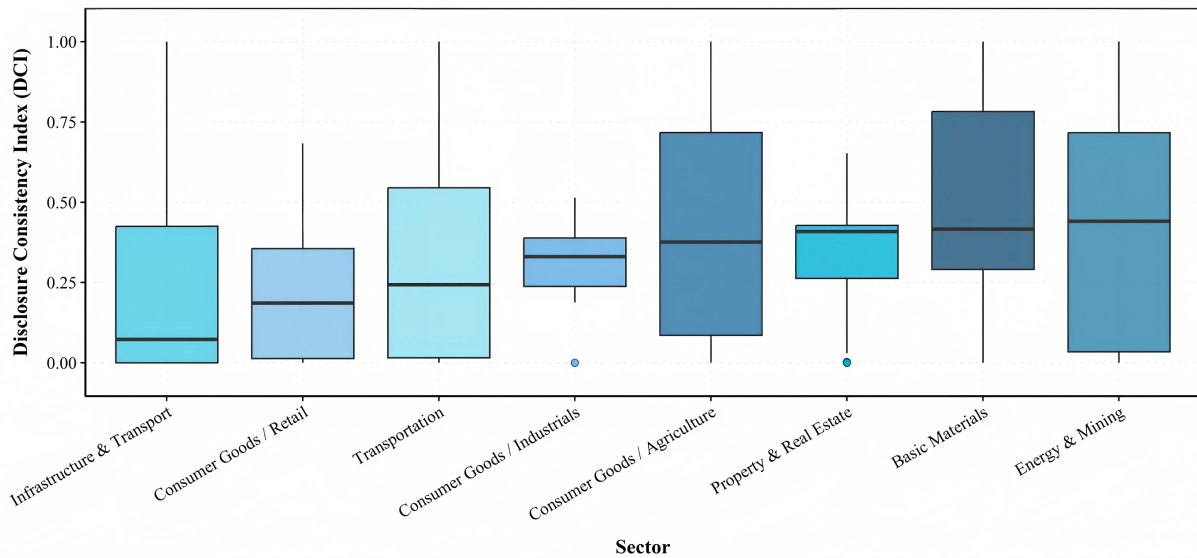


Figure 5. DCI distribution by industry sector (N = 83 companies, 314 observations).

Table 3. Dunn's post-hoc pairwise comparisons of DCI by sector.

Sector Pair	p (Adj., BH)	Significant ($\alpha = 0.05$)
Cons. Goods/Agriculture vs. Infrastructure & Transport	0.004	Yes
Basic Materials vs. Cons. Goods/Retail	0.024	Yes
Cons. Goods/Retail vs. Energy & Mining	0.024	Yes
Basic Materials vs. Infrastructure & Transport	<0.001	Yes
Energy & Mining vs. Infrastructure & Transport	<0.001	Yes
Cons. Goods/Agriculture vs. Cons. Goods/Retail	0.121	No
Basic Materials vs. Property & Real Estate	0.307	No
Infrastructure & Transport vs. Property & Real Estate	0.307	No
Energy & Mining vs. Property & Real Estate	0.337	No
Basic Materials vs. Cons. Goods/Agriculture	0.513	No
Basic Materials vs. Cons. Goods/Industrials	0.513	No
Basic Materials vs. Transportation	0.513	No
Cons. Goods/Agriculture vs. Energy & Mining	0.513	No
Cons. Goods/Agriculture vs. Property & Real Estate	0.513	No
Cons. Goods/Industrials vs. Cons. Goods/Retail	0.513	No
Cons. Goods/Industrials vs. Energy & Mining	0.513	No
Cons. Goods/Industrials vs. Infrastructure & Transport	0.513	No
Cons. Goods/Retail vs. Property & Real Estate	0.513	No
Energy & Mining vs. Transportation	0.513	No
Infrastructure & Transport vs. Transportation	0.513	No
Cons. Goods/Agriculture vs. Cons. Goods/Industrials	0.630	No
Cons. Goods/Retail vs. Transportation	0.630	No
Cons. Goods/Agriculture vs. Transportation	0.720	No
Cons. Goods/Retail vs. Infrastructure & Transport	0.897	No
Basic Materials vs. Energy & Mining	0.916	No
Cons. Goods/Industrials vs. Property & Real Estate	0.984	No
Cons. Goods/Industrials vs. Transportation	0.984	No
Property & Real Estate vs. Transportation	0.984	No

3.5. K-Means Clustering Results

Clustering on a single scalar variable (mean DCI) does not leverage K-means' multivariate capabilities; this section reports the clustering analysis in two stages. **Figure 6a** re-

produces the original univariate approach (mean DCI only) for reference. In contrast, **Figure 6b** presents the bivariate clustering on mean DCI and mean ENV_AVG (the aggregate environmental disclosure level), which jointly captures disclosure consistency and disclosure volume.

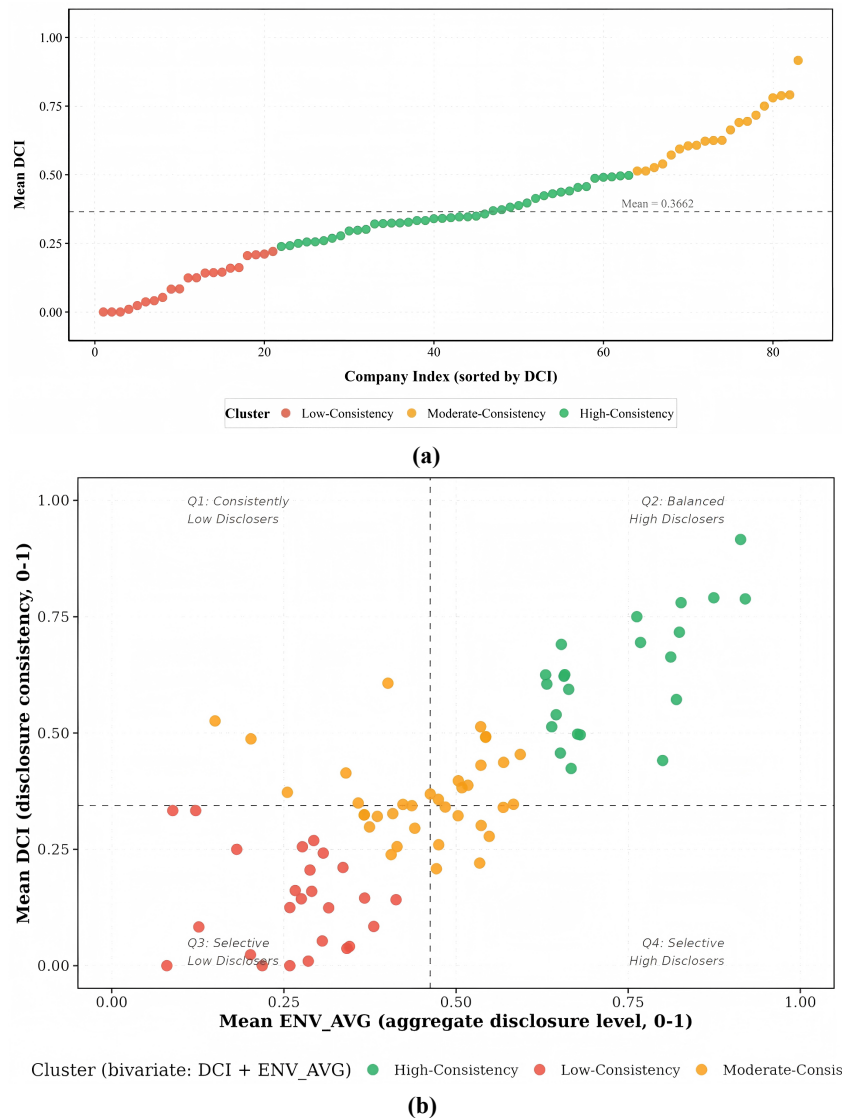


Figure 6. (a) K-means clustering results (univariate, original approach): 83 companies by mean DCI; (b) K-means clustering results (revised, bivariate): DCI vs. ENV_AVG quadrant scatter.

The overall mean DCI across all companies was 0.3662 (company-level average). Under the original univariate clustering (**Figure 6a**), three clusters were identified: Low-Consistency (N = 21, mean DCI range 0.00–0.22), Moderate-Consistency (N = 42, mean DCI range 0.24–0.50), and High-Consistency (N = 20, mean DCI range 0.51–0.92).

Under the bivariate clustering (**Figure 6b**, mean DCI and mean ENV_AVG jointly), three clusters again emerge:

Low-Consistency (N = 25, mean DCI = 0.137, mean ENV_AVG = 0.265, dominated by Infrastructure & Transport), Moderate-Consistency (N = 36, mean DCI = 0.366, mean ENV_AVG = 0.450, dominated by Consumer Goods/Agriculture and Property & Real Estate), and High-Consistency (N = 22, mean DCI = 0.627, mean ENV_AVG = 0.735, dominated by Energy & Mining and Basic Materials).

Cluster membership is substantially, though not per-

fectly, preserved across the two specifications: 67 of 83 companies (80.7%) retain the same cluster label under both the univariate and bivariate approaches, indicating that the bivariate re-analysis refines rather than overturns the original typology.

In this sample, DCI and ENV_AVG are positively associated at the company level (Spearman's $\rho = 0.692$ at the firm-year level; see Section 4.4), so the quadrants populated most heavily are Q3 (Selective Low Disclosers) and Q2 (Balanced High Disclosers), with fewer firms falling into the conceptually distinct Q1 (Consistently Low Disclosers, i.e.,

uniformly minimal disclosure) and Q4 (Selective High Disclosers, i.e., high volume but imbalanced) categories, highlighting that while DCI and disclosure volume are correlated in this sample, they remain conceptually and empirically distinguishable, consistent with Section 4.2's discussion of what DCI does and does not capture.

3.6. Optimal K: Elbow and Silhouette Method

Figure 7 presents two complementary methods for determining the optimal number of clusters.

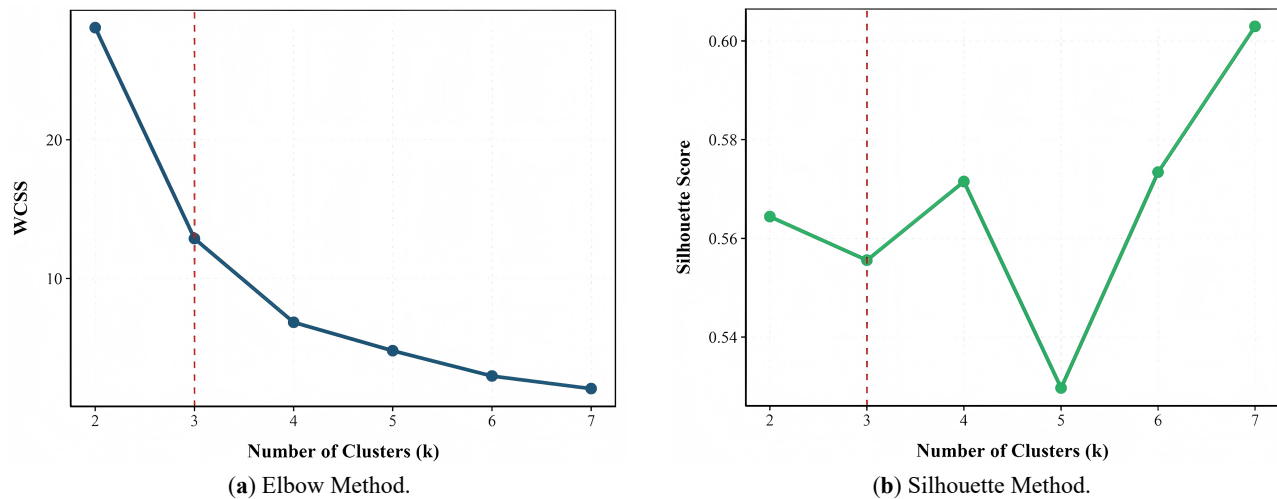


Figure 7. Elbow Method (WCSS) and Silhouette Method for optimal k determination.

The Elbow Method (Figure 7a) shows the pronounced inflection in the Within-Cluster Sum of Squares (WCSS) at $k = 3$. The Silhouette Method (Figure 7b) shows a local maximum at $k = 4$ (score ≈ 0.57) but maintains an interpretable score at $k = 3$ (≈ 0.555).

As an additional validation check, the Gap Statistic^[20] ($B = 100$ bootstrap reference sets) was computed; using the conservative firstSEmax rule, it selects $k = 1$ as optimal, indicating that the mean-DCI-based clustering structure is statistically weak and that firms are better characterized as lying along a continuous consistency gradient than as forming sharply separated groups. This result is consistent with a key methodological limitation raised in peer review: clustering firms on a single scalar variable (mean DCI) is unlikely to recover well-separated, multivariate clusters, since K-means is designed for, and most reliably validated on, multidimensional feature spaces.

Given the balance between statistical parsimony and

substantive interpretability, $k = 3$ was selected as the final clustering solution. It was retained as the reported solution because it offers a parsimonious and substantively interpretable typology (Low-, Moderate-, and High-Consistency) that is useful for the illustrative and communicative purposes of Section 3.7, and because the elbow and silhouette diagnostics both support it as a locally reasonable choice. However, this typology should be read as a descriptive segmentation of the DCI distribution rather than as evidence of genuine multivariate sub-populations of firms, and readers should treat the boundaries between clusters as indicative rather than statistically sharp.

3.7. Environmental Sub-Pillar Profiles by Cluster

Figure 8a presents a heatmap of average GRI sub-pillar disclosure scores for each of the three clusters. Figure 8b

below presents the same underlying results as a grouped bar chart with 95% bootstrap confidence intervals ($B = 1,000$ resamples per cluster-pillar combination), and additionally conveys the statistical uncertainty around each cluster mean.

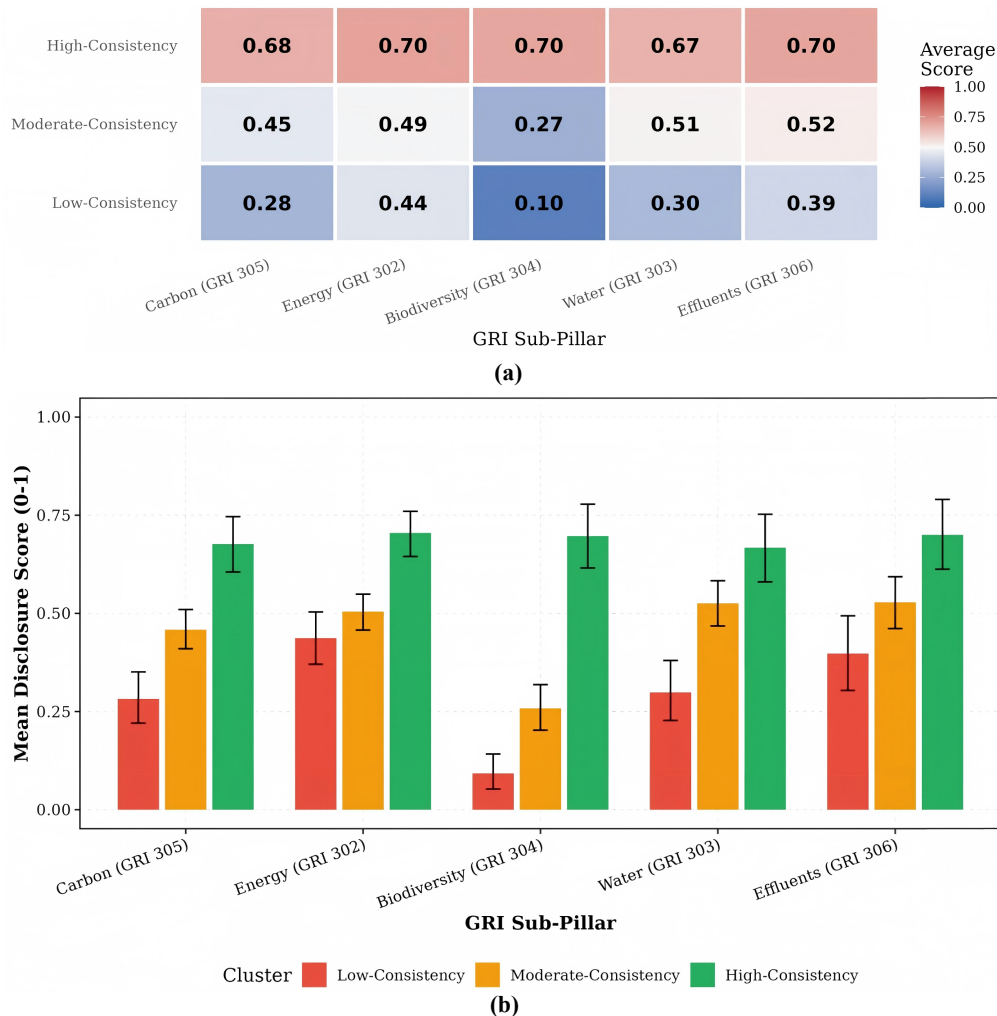


Figure 8. (a) Environmental sub-pillar profile by cluster—heatmap (average scores 0–1); (b) Environmental sub-pillar profile by cluster—grouped bar chart with 95% bootstrap confidence intervals ($B = 1,000$).

Figure 8 shows that the three clusters differ mainly in overall disclosure levels across all five sub-pillars rather than in the relative shape or balance among pillars. The High-Consistency cluster scores highest on every sub-pillar (Carbon ≈ 0.68 , Energy ≈ 0.70 , Biodiversity ≈ 0.70 , Water ≈ 0.67 , Effluents ≈ 0.70), the Low-Consistency cluster scores lowest on every sub-pillar (Carbon ≈ 0.28 , Energy ≈ 0.44 , Biodiversity ≈ 0.10 , Water ≈ 0.30 , Effluents ≈ 0.39), and the Moderate-Consistency cluster falls in between on all five dimensions (Carbon ≈ 0.45 , Energy ≈ 0.49 , Biodiversity ≈ 0.27 , Water ≈ 0.51 , Effluents ≈ 0.52).

This pattern indicates that the $k = 3$ typology, as operationalized here, primarily separates firms by overall dis-

closure volume rather than by distinct disclosure “shapes,” a nuance that qualifies the cluster labels (“Low/Moderate/High-Consistency”) and reinforces the point that DCI-based measures of consistency can be difficult to disentangle from measures of disclosure quantity. Biodiversity nonetheless shows the widest absolute gap between the Low- and High-Consistency clusters (0.10 vs. 0.70), reaffirming it as the sub-pillar most responsible for within-firm imbalance.

Table 4 synthesizes the updated bivariate K-means cluster typology, integrating mean DCI ranges, aggregate environmental score level (ENV_AVG), dominant sector distributions, and targeted policy recommendations.

Table 4. K-means cluster typology summary (revised: bivariate clustering on mean DCI and mean ENV_AVG).

Cluster	Label	N	Mean DCI (Range)/Mean ENV_AVG	Dominant Sector(s)	Policy Recommendation
1	Low-Consistency	25	0.137 (0.00–0.33)/0.265	Infrastructure & Transport (10); Consumer Goods/Retail (4); Energy & Mining (4)	Targeted regulatory audit; GRI 304/306 capacity building
2	Moderate-Consistency	36	0.366 (0.21–0.61)/0.450	Consumer Goods/Agriculture (10); Property & Real Estate (7)	SEOJK compliance monitoring; GRI 303 improvement focus
3	High-Consistency	22	0.627 (0.42–0.92)/0.735	Energy & Mining (9); Basic Materials (6)	NZE 2060 benchmarking; role model for peer sectors

4. Discussion

4.1. Selective Disclosure and Biodiversity Gaps

The finding that Biodiversity (GRI 304) consistently recorded the lowest disclosure score and the slowest growth trajectory (CAGR $\approx$ 16.34%/year (2020–2023)) is not merely a statistical observation; it is consistent with, though not direct proof of, a broader pattern of selective or opportunistic disclosure documented in the literature. Reporting on GRI 304 requires company-specific ecological surveys, habitat mapping, and multi-stakeholder coordination of qualitatively different data-collection burdens, unlike electricity bill aggregation for GRI 302^[6], which offers a plausible operational explanation for the lag independent of any deliberate withholding.

The acceleration in Carbon (GRI 305) and Waste (GRI 306) disclosures between 2021 and 2022 coincided with SEOJK 16/2021, which is consistent with the hypothesis that regulatory specificity influences disclosure prioritization^[5,13]. However, this study's descriptive, non-causal design cannot rule out concurrent trends (e.g., broader ESG market pressure) as alternative explanations, though future quasi-experimental analysis could help establish causal attribution. This interpretation should be read as consistent with, rather than proof of, legitimacy-theory-based motives.

Through a legitimacy-theory lens, one plausible reading is that firms prioritize disclosures most closely monitored by regulators and stakeholders. However, intrinsic environmental commitment cannot be ruled out as a contributing factor, given the available data^[9]. These findings are consistent with selective disclosure behavior discussed in Section 1.3.

4.2. DCI as a Multidimensional Cohesion Index

The bimodal distribution reveals a bifurcated disclosure regime within the IDX-listed universe. A substantial proportion of firms disclose comprehensively and relatively consistently across all five sub-pillars, while a comparable

proportion focuses almost exclusively on one or two dimensions. This bimodality is entirely invisible in aggregate ESG or total GRI scores, validating the fundamental methodological argument of this study.

It is important to emphasize what DCI does and does not capture: DCI measures the internal balance (consistency) of disclosure across the five sub-pillars, not the completeness or substantive quality of that disclosure. A firm that discloses only 20% of items in each of the five sub-pillars would register a DCI close to 1 (perfectly balanced), despite very low overall disclosure. In contrast, a firm disclosing 90% in four sub-pillars but 10% in one would register a comparatively low DCI despite substantially higher average disclosure. High-DCI firms in this sample are therefore best described as consistent disclosers, not necessarily comprehensive or high-quality disclosers, and DCI is intended as a complement to, not a replacement for, existing GRI compliance or ESG quality scores.

The weak Pearson correlation between Biodiversity and Effluents ($r = 0.26$) confirms that different institutional logics drive these sub-pillars and cannot be analytically consolidated without information loss. Similarly, Saraswati et al., in the *International Journal of Energy Economics and Policy*, found that virtually every Indonesian firm has at least one ESG pillar where it underperforms, providing a direct empirical justification for the multidimensional approach operationalized by the DCI^[8].

4.3. Sectoral Heterogeneity and Regulatory Implications

The observed sectoral heterogeneity in DCI indicates that industry-specific operational logic is a stronger determinant of disclosure balance than regulatory mandates alone. This is in line with Wicaksono, who found that stakeholder pressure is a major driver of environmental disclosure among Southeast Asian mining companies^[21]. A tentative implication is that a uniform instrument, such as POJK 51, alone may not be sufficient to achieve cross-sectoral parity in dis-

closure balance. However, this study does not directly test intervention effects. Sector-specific standards analogous to the EU's Corporate Sustainability Reporting Directive (CSRD) double-materiality requirements could be worth exploring for high-impact sectors such as Energy & Mining and Infrastructure. Still, we present this as a direction for future policy research rather than a firm recommendation, since this study does not evaluate the costs, feasibility, or unintended consequences of such standards^[14,21,22].

Several institutional factors may explain the observed sectoral heterogeneity, although these explanations remain interpretive rather than causally tested. The following examples illustrate this pattern across three sectors:

Infrastructure & Transport (Low DCI): This sector's low consistency likely reflects the nature of its regulatory environment. Infrastructure companies face environmental disclosure requirements primarily through project-based Environmental Impact Assessment (AMDAL) regulations rather than consolidated GRI standards. The absence of sector-specific environmental sub-pillar guidance under POJK 51 means disclosure is driven by project-level compliance rather than firm-level GRI balance, resulting in fragmented reporting patterns. This is consistent with Tibshirani et al.^[20], who found that stakeholder pressure, rather than regulatory requirements, is the primary driver of disclosure in capital-intensive infrastructure sectors.

Consumer Goods/Agriculture (Higher DCI): Firms in this sector face supply chain sustainability pressures from international buyers and commodity certification bodies (e.g., RSPO for palm oil, FSC for timber), creating cross-pillar reporting incentives beyond domestic regulatory requirements. These multi-stakeholder pressures operate simultaneously across energy, water, biodiversity, and waste dimensions, which correspond to the sub-pillars measured by DCI, producing more balanced disclosure portfolios^[7].

Energy & Mining (Moderate-to-Low DCI, High Variance): This sector shows the widest DCI dispersion, reflecting a bifurcated population: large state-owned enterprises (BUMN) subject to high stakeholder scrutiny with relatively comprehensive reporting, and mid-sized extractive firms primarily driven by SEOJK 16/2021 carbon disclosure requirements, which create asymmetric incentives favoring GRI 305 while neglecting GRI 304.

These sector-level readings are offered as plausible in-

stitutional context for the observed heterogeneity rather than as a tested causal mechanism.

4.4. Robustness and Limitations

Robustness was assessed through several complementary checks, which consistently support the stability of the proposed DCI. Because the analytic sample used in this study (companies with complete five sub-pillar data in all observed years) already excludes cases with missing pillar scores, list-wise deletion and multiple imputation are, by construction, identical for this sample. Alternative sensitivity analyses and multicollinearity diagnostics further confirmed that the reported DCI values are stable and that no severe multicollinearity exists among the five GRI sub-pillars.

Convergent validity of the DCI was further examined by comparing it against two alternative consistency measures computed on the same five sub-pillars: a Shannon-entropy-based evenness index and a Gini-coefficient-based consistency index ($1 - \text{Gini}$). DCI correlated strongly with both ($r = 0.741$ and $r = 0.927$, respectively; both $p < 0.001$), indicating that the index captures a construct similar to that of established dispersion-based measures rather than an idiosyncratic artifact of the CV formulation. The distributional and truncation checks reported in Sections 2.4 and 3.2 further support the interpretation of the DCI and highlight its dependence on lower-bound truncation in the presence of highly uneven observations.

These findings suggest that the DCI captures a consistency construct comparable to other dispersion-based measures, rather than being an artifact of the CV formulation alone. At the same time, the positive relationship between DCI and ENV_AVG indicates that disclosure consistency and disclosure volume are related, although they do not represent the same concept. Therefore, the DCI is better interpreted as a complementary measure to aggregate environmental disclosure scores, rather than as a substitute for them.

Overall, the sensitivity analysis, bootstrap confidence intervals, convergent validity assessment, and clustering diagnostics support the stability of the DCI. However, the mixed evidence from the clustering diagnostics suggests that the three-cluster solution should be viewed as a descriptive and interpretable segmentation rather than as evidence of clearly separated statistical groups.

From a practical perspective, the DCI may serve as an

initial screening tool for regulators to identify companies whose environmental disclosures are concentrated in only a few sub-pillars. A low DCI should not be interpreted directly as evidence of non-compliance or greenwashing, but it may indicate the need for closer review of underreported environmental dimensions. For ESG investors and analysts, the DCI provides additional information beyond aggregate environmental scores by showing whether disclosures are distributed relatively evenly across the five environmental sub-pillars. For companies, the index may also be useful as an internal diagnostic tool to identify disclosure gaps before reports are published.

Key limitations include: (1) DCI's sensitivity to near-zero mean scores and its reliance on truncation at the lower bound, only partially mitigated through ϵ -stabilization; (2) the index measures disclosure quantity/balance rather than substantive quality; (3) the four-year, unbalanced panel limits long-term trend inference; and (4) generalizability is bounded to large-cap IDX-listed firms^[23,24].

Regarding generalizability, the DCI framework is, in principle, applicable to any context in which a firm's sustainability disclosure is evaluated across multiple standardized sub-dimensions reported on a common scale; the GRI framework's global adoption makes DCI technically transferable to other GRI-reporting jurisdictions, including ASEAN markets with emerging mandatory ESG reporting regimes (e.g., Bursa Malaysia, SGX Singapore, SET Thailand) and the EU under CSRD double-materiality reporting, where the reported topics map closely onto the five GRI sub-pillars used here.

This transferability, nonetheless, remains untested in the present study and is bounded by at least three conditions: (1) DCI construction requires sub-dimensions sharing a common measurement scale, so contexts using heterogeneous scoring systems would require prior normalization; (2) the epsilon winsorization threshold may need recalibration for different missing-data patterns; and (3) the sector typologies used here reflect Indonesia's IDX classification and may not map directly onto other exchanges' classifications.

4.5. Theoretical Contributions

This study operationalizes legitimacy theory, stakeholder theory, and agency theory not by claiming to extend them as a new theoretical perspective, but rather by proposing and validating a new measurement instrument, the DCI,

which operationalizes constructs implied by these existing frameworks. Through a legitimacy-theory lens, DCI demonstrates that corporate legitimation operates not only through disclosure but also through selective dimensionality. Companies choose which sub-pillars to disclose in line with those that stakeholders most visibly monitor, although this study does not directly test the legitimation mechanism itself. This interpretation is consistent with Marquis et al., who showed that companies may emphasize favorable environmental information while limiting the disclosure of less favorable information^[7]. In the present study, the relatively low level of biodiversity disclosure compared with carbon, energy, and waste reflects a pattern that is consistent with selective dimensional disclosure. However, it does not prove deliberate managerial intent.

From a stakeholder-theory perspective, the sectoral differences in DCI suggest that disclosure balance may also be shaped by differences in stakeholder pressure and the relative importance of environmental issues across industries^[13,17,21].

In agency theory, DCI serves as a proxy for the degree to which disclosure strategies are applied uniformly versus selectively across sub-pillars. Higher DCI may signal more uniform information provision, potentially associated with reduced information asymmetry, whereas lower DCI indicates greater concentration of disclosure across specific dimensions. Whether this uniformity translates into reduced information asymmetry remains an empirical question. Future research linking DCI to information asymmetry proxies (e.g., bid-ask spreads or analyst forecast dispersion) would need to establish this link. In this sense, the DCI complements aggregate ESG or GRI scores by showing whether environmental information is disclosed relatively evenly across the five sub-pillars. The distinction allows future studies to examine whether disclosure balance has consequences that differ from those associated with disclosure volume alone. Ultimately, DCI is a theoretically reproducible measurement instrument that future studies can incorporate as an independent variable in studies testing disclosure balance against cost of capital, firm valuation, or ESG investor reactions^[25–27].

5. Conclusion

This study presents the first empirical application of the Disclosure Consistency Index (DCI) to measure multi-

dimensional environmental disclosure consistency among companies listed on the Indonesia Stock Exchange (IDX). Using a panel dataset comprising 83 companies and 314 firm-level observations from 2020 to 2023, which covers the five environmental sub-pillars of the GRI, this study shows that Indonesian listed firms continue to disclose environmental information selectively and unevenly despite the regulatory scaffolding of POJK 51/2017 and SEOJK 16/2021.

The key finding of this study is that the aggregate ESG score systematically masks disclosure imbalances within companies. The average DCI index value of 0.3704 (median = 0.3552) and the bimodal distribution centered around DCI = 0 and DCI = 1 reveal a structurally dispersed pattern of disclosure. Specifically, Biodiversity (GRI 304) consistently records the lowest scores and growth rates, while Carbon and Effluents benefit from higher regulatory specificity. Sectoral differences are significant across eight industry categories. K-means clustering identified three actionable firm typologies: Low, High, and Moderate-Consistency, each corresponding to distinct disclosure profiles and policy priorities. Overall, the DCI framework provides an empirical tool for verifying and substantiating existing theoretical propositions regarding selective disclosure, legitimacy management, and information asymmetry in future research.

This study is limited by DCI's sensitivity to mean scores near zero, which is mitigated by ϵ -winsorization. In addition, the index measures the quantity of disclosure rather than the quality of substantive disclosure, the four-year panel limits inference about long-term trends, and the findings are restricted to large companies listed on the Indonesia Stock Exchange.

Despite the limitations, the DCI framework demonstrates diagnostic potential for identifying patterns of voluntary disclosure. For regulators (OJK), the DCI offers a potentially complementary compliance indicator for detecting selective disclosure patterns that are not visible in aggregate score-based evaluations. Piloting and validating a minimum DCI threshold, rather than adopting one immediately, would be a reasonable next step before any revision of POJK 51 or SEOJK 16, given that this study has not tested how such a threshold would perform or what unintended effects it might have. For ESG investors and fund managers, integrating DCI as an additional screening layer may reduce exposure to greenwashing risks, particularly in investment portfolios

in the resource-extraction sector. However, it should be used alongside, not in a place of, existing risk indicators. For academic researchers, the DCI framework is a reproducible instrument that can be extended to other ASEAN markets and tested in relation to financial outcomes. To build upon these findings, we recommend that future studies: (1) test the association between DCI levels and environmental performance indicators (e.g., actual emissions reduction, biodiversity impact); (2) conduct threshold analysis using receiver operating characteristic (ROC) methods to identify DCI cut-points with optimal sensitivity and specificity for greenwashing detection; and (3) examine whether DCI levels are associated with cost of capital, market valuation premiums, or institutional investor ownership concentration, conducting empirical tests that would establish the business case for disclosure balance beyond regulatory compliance.

Author Contributions

Conceptualization, A.D.S. and J.H.; methodology, A.D.S. and A.F.A.; software, A.S.R.; validation, A.D.S. and A.F.; formal analysis, A.S.R.; investigation, A.S.R.; resources, A.S.R.; data curation, A.D.S. and A.S.R.; writing—original draft preparation, A.D.S.; writing—review and editing, A.D.S. and A.S.R.; visualization, A.S.R.; supervision, A.D.S.; project administration, A.D.S.; funding acquisition, A.D.S. All authors have read and agreed to the published version of the manuscript.

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Informed Consent Statement

Not applicable.

Data Availability Statement

Data is available upon request.

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Conflicts of Interest

The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

AI Use Statement

During the preparation of this manuscript, the authors used Perplexity, Claude and Anthropic solely for ideas extraction and language refinement. No AI tools were used for data analysis, interpretation, or generation of scientific content. All outputs were carefully reviewed and edited by the authors. The authors take full responsibility for the integrity and accuracy of the work.

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