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Driving Sustainable Performance in the Digital Era: The Roles of Big Data Analytics, Green Investment, and Green Transformational Leadership

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ABSTRACT
The global sustainability paradox highlights the gap between extensive investments in digital transformation and green initiatives and the limited achievement of Sustainable Development Goals (SDGs), particularly in emerging economies such as Indonesia. Prior studies have largely examined Big Data Analytics (BDA) and Green Investment (GI) separately, producing inconsistent findings and offering limited insight into the role of leadership as a contextual factor. This study aims to analyze the effects of BDA and GI on Sustainable Performance (SP) and to evaluate the moderating role of Green Transformational Leadership (GTL) in Indonesian non-financial listed companies. This research adopts a quantitative design using panel data from 741 firm-year observations over the 2023–2024 period. Data were collected from annual and sustainability reports and measured using a content analysis–based disclosure index that captures the extent and quality of sustainability-related information. The hypotheses were tested through panel regression with interaction terms to examine moderation effects. The results indicate that both BDA and GI have significant positive impacts on SP. Furthermore, GTL not only directly enhances sustainability performance but also strengthens the effects of BDA and GI, confirming its role as a quasi-moderating variable. These findings suggest that leadership is a critical mechanism in translating digital capabilities and environmental investments into tangible sustainability outcomes. This study extends the Natural Resource-Based View and Dynamic Capabilities Theory by demonstrating the catalytic role of environmentally oriented leadership. Practically, it emphasizes the importance of aligning digital strategy, green investment, and leadership development to improve corporate sustainability performance.

Keywords: *Big Data Analytics, Green Investment, Sustainable Performance, Green Transformational Leadership, Green Knowledge Management*

1. Introduction

The global corporate sustainability landscape reveals a striking paradox: while organizations worldwide invest trillions in digital transformation and green initiatives, only a small fraction successfully achieve comprehensive Sustainable Development Goals (SDGs) targets (OECD, 2024). This challenge is even more pronounced in emerging economies, where Indonesia's Environmental Performance Index ranks 164th out of 180 countries, signalling a persistent sustainability performance gap in the corporate sector. In response, Indonesia has strengthened sustainability governance through POJK 51/2017 and SEOJK 16/2021, which intensify expectations for sustainability disclosure, risk management, and accountability particularly for listed companies with material environmental and social impacts.

At the company level, this global challenge requires firms to transform their business models. Sustainable Performance (SP) refers to an organization's capacity to attain financial success concurrent with advancing ecological integrity and societal well-being, constituting a competitive edge that rivals find challenging to replicate and that remains indispensable for enduring organizational viability. In the Indonesian context, although firms are increasingly

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adopting advanced digital technologies and environmental programmes, empirical evidence shows that most executives acknowledge failing to leverage big data analytics effectively for sustainability and that green investment still represents a relatively minor share of total national investment (Peraturan Otoritas Jasa Keuangan RI, 2023; Sternfels, 2021). This disconnects between technological capability, financial commitment, and realised sustainability outcomes raises fundamental questions about the missing catalysts in the sustainability transformation process.

Attaining exceptional sustainability outcomes necessitates that corporations harness two pivotal strategic assets. The first is Big Data Analytics (BDA), which embodies the organizational capacity to analyze vast and diverse datasets instantaneously, thereby facilitating more efficient resource utilization and lower carbon footprints. Second, Green Investment (GI) reflects the financial commitment to environmental initiatives, including clean technologies and sustainable infrastructure. Big data analytics, with its ability to process large, complex and heterogeneous data in real time, offers substantial potential to optimise resource utilisation, reduce emissions and waste, and improve operational efficiency (Halbusi et al., 2024). Firms that effectively deploy big data capabilities report considerable improvements in resource productivity and waste reduction, demonstrating the tangible benefits of data-driven sustainability strategies (Alyahya et al., 2023). At the same time, green investment is gaining momentum as stakeholders increase demands for environmental accountability, with sustainable assets rapidly expanding in global capital markets (Ye & Dela, 2023).

Nevertheless, the extant scholarly literature reveals conflicting empirical evidence (equivocal outcomes) concerning the impact of BDA and GI on sustainability outcomes. Certain investigations demonstrate robust favorable impacts, whereas alternative studies identify negligible or absent associations. Such discrepancies point to the existence of contextual determinants that shape and condition these linkages. Green Transformational Leadership (GTL) emerges as a critical moderating mechanism that may determine when and to what extent technological and financial resources translate into superior sustainable performance. In Indonesia, non-financial listed companies particularly those in environmentally intensive industries face escalating regulatory pressures from POJK 51/2017 and SEOJK 16/2021 to disclose and manage their environmental impacts, while simultaneously being expected to maintain financial performance and shareholder value (Ramadana et al., 2025). Nevertheless, the translation of digital and financial resources into measurable sustainable performance remains uneven, reinforcing the need to examine leadership as a boundary condition that shapes implementation quality, employee commitment, and the strategic alignment of sustainability initiatives.

Notwithstanding the expanding volume of scholarly work, notable lacunae persist in comprehending the combined mechanisms through which big data analytics and green investment collectively shape sustainability outcomes. Prior studies have predominantly examined either big data analytics or green investment in isolation, often focusing on specific industries or single-country contexts. Empirical findings are mixed: some studies report that big data analytics strengthens sustainable performance through improved decision-making, circular economy practices and enhanced environmental monitoring, whereas others find weak or insignificant direct effects (Edwin Cheng et al., 2022; Sangpetch & Ueasangkomsate, 2023). Similarly, research on green investment has produced inconsistent results, with some evidence suggesting positive effects on sustainability outcomes and other studies detecting no significant relationship (Indriastuti & Chariri, 2021a; Nunik Nurmalasari & Sri Dwi Kania, 2024). Although green transformational leadership is increasingly recognised as a potential catalyst, it has rarely been tested as a moderating mechanism in the relationship between big data analytics, green investment and sustainable performance (Bhatti et al., 2023; Zhao & Huang, 2022). What distinguishes the current investigation from preceding scholarly efforts is the introduction of Green Transformational Leadership as a contingency variable that delineates the specific circumstances governing how BDA and GI influence sustainability outcomes. Additionally, this research integrates Green Knowledge Management and Green Talent Management as covariates to prevent specification errors arising from excluded relevant predictors.

Consequently, this investigation seeks to construct and empirically validate a comprehensive framework that scrutinizes the influence of big data analytics and green investment on sustainability outcomes, while simultaneously exploring how green transformational leadership acts as a boundary condition governing these associations. Specifically, this study pursues three objectives: first, to investigate the immediate impacts of big data analytics and green investment on sustainability outcomes utilizing longitudinal data from non-financial corporations registered on the Indonesia Stock Exchange; second, to appraise the conditioning influence of green transformational leadership on the association between big data analytics and sustainability outcomes; and third, to evaluate how green transformational leadership shapes the connection between green investment and sustainability outcomes. This investigation endeavors to scrutinize the impacts of BDA and GI on SP while appraising the conditioning function of GTL within these associations. The outcomes are anticipated to assist investors in appraising organizations that proficiently capitalize on digital and environmental assets under robust sustainability-focused leadership governance. Aligned with these stated aims, the investigation addresses the subsequent scholarly inquiries: (1) How do big data analytics and green investment individually affect sustainable performance in Indonesian non-financial companies? (2) In what manner and to what degree does green transformational leadership condition the association linking big data analytics to sustainability outcomes? and (3) How does green transformational leadership influence the effect of green investment on sustainable performance?

Grounded in the aforementioned objectives and scholarly inquiries, this investigation goes beyond merely testing whether BDA and GI improve sustainability outcomes; it further elucidates the reasons underlying inter-firm variation in these effects by formally incorporating Green Transformational Leadership (GTL) as a contingency mechanism. By doing so, the research responds to the mixed findings in prior studies and offers a more context-sensitive understanding of how digital and green resources are converted into firm-level sustainability outcomes in emerging-market settings.

This research makes several theoretical and practical contributions. From a theoretical perspective, it extends the Natural Resource-Based View by demonstrating how technological capabilities (big data analytics) and financial resources (green investment) interact with leadership dynamics to create sustainable performance advantages in an emerging market context (Hart, 2017; Hart & Dowell, 2011). The study also operationalises green transformational leadership as a dynamic capability that orchestrates and reconfigures resources, thereby enriching the Dynamic Capabilities perspective (Teece, 2007). By explicitly modelling and testing moderation effects, the research helps reconcile contradictory findings in prior empirical studies and clarifies the boundary conditions under which big data analytics and green investment translate into superior sustainable performance. To strengthen internal validity, this study further incorporates Green Knowledge Management and Green Talent Management as control variables to mitigate potential omitted variable bias.

From a practical standpoint, the outcomes are anticipated to furnish empirically grounded recommendations for corporate leaders aiming to optimize the yield from their digital and sustainability expenditures through strategic alignment with leadership capacity building and environmentally conscious organizational routines. For governmental authorities and regulatory bodies, the investigation highlights the necessity of supplementing fiscal and technological stimulus measures with initiatives that cultivate environmentally conscious leadership competencies and governance frameworks supporting more effective implementation of sustainability agendas under regulatory pressures such as POJK 51/2017 and SEOJK 16/2021.

The subsequent portions of this manuscript are organized in the following manner. The second section elaborates on the theoretical underpinnings and hypothesis formulation, weaving together the Natural Resource-Based View, transformational leadership theory, and dynamic capabilities perspectives into a unified conceptual model. The third section outlines the research methodology, encompassing sample determination, construct operationalization via content analysis, and panel data analytical procedures. The fourth section presents the empirical findings, and the fifth section interprets these results within the context of the theoretical architecture and existing scholarly evidence. The sixth section concludes by underscoring principal implications, recognizing study constraints, and charting avenues for subsequent scholarly inquiry in sustainability performance management.

2. Literature Review

Theoretical Foundation

The current investigation synthesizes three mutually reinforcing theoretical lenses the Natural Resource-Based View (NRBV), Dynamic Capabilities Theory (DCT), and Transformational Leadership Theory (TLT) while consolidating contemporary empirical evidence to elucidate the mechanisms through which big data analytics (BDA) and green investment (GI) determine sustainability outcomes (SP) as conditioned by green transformational leadership (GTL).

The NRBV broadens the conventional Resource-Based View by elevating environmental limitations and ecological factors to central determinants of strategic direction, rather than treating them as secondary concerns. NRBV posits that firms develop distinctive environmental capabilities such as pollution prevention, product stewardship, and sustainable development that can evolve into sources of sustained competitive advantage when they are valuable, rare, inimitable, and well organized (Hart, 2017; Hart & Dowell, 2011). In this study, BDA is interpreted as a technological capability that enables pollution prevention and resource optimization through real-time monitoring and predictive analytics, while GI represents financial commitments that support sustainable development through clean technologies, eco-innovation, and long-term environmental projects. Within developing market economies like Indonesia, where governmental mandates and public demands regarding ecological accountability are progressively escalating, NRBV provides a useful lens to understand why firms that invest in digital and green capabilities may attain superior SP.

DCT complements NRBV by shifting attention from static resource endowments to the organizational processes that enable firms to sense opportunities and threats, seize them through timely investment, and transform or reconfigure existing assets and capabilities to remain competitive in changing environments (Teece, 2007). From a DCT perspective, BDA and GI are important but potentially underutilized resources unless firms possess dynamic capabilities to integrate, coordinate, and reconfigure them in response to sustainability challenges. In this study, GTL is conceptualized as a higher-order dynamic capability that orchestrates how technological and financial resources are deployed for sustainability objectives. Leaders with strong green transformational qualities help their organizations interpret sustainability-related signals, prioritize strategic responses, and realign structures, systems, and culture to support the effective use of BDA and GI.

TLT provides the behavioral foundation for understanding how leadership shapes followers' motivation and collective commitment to long-term goals that transcend short-term self-interest (Bass & Riggio, 2006). The four foundational pillars of this theory charismatic role modeling, motivational vision articulation, cognitive challenge provision, and personalized developmental attention are readily applicable to ecological settings, giving rise to the concept of GTL. Green transformational leaders articulate a compelling environmental vision, challenge existing routines, encourage eco-innovation, and support employees in developing green competencies (Chen & Chang, 2013). In this study, GTL is expected to directly enhance SP and to strengthen the degree to which BDA and GI are converted into concrete sustainability achievements by guaranteeing that analytically derived insights and environmental initiatives are genuinely executed rather than remaining at the planning stage.

Prior Research Synthesis

Recent empirical research on SP can be grouped into three major streams that align with these theoretical lenses: (1) technology-enabled sustainability, (2) green investment and financial–environmental outcomes, and (3) leadership and sustainability performance. In the first stream, studies on BDA and sustainability report mixed findings. (Sangpetch & Ueasangkomsate, 2023) show that BDA enhances SP indirectly through circular economy practices among Thai SMEs, while (Edwin Cheng et al., 2022) find that BDA affects SP only via circular economy and supply chain flexibility, with no direct effect. (Alyahya et al., 2023) report that BDA capabilities improve economic, social, and environmental performance via strategic agility and creativity, and (Alshuaibi et al., 2024) find that BDA, green human resource management, and green digital learning strengthen green innovation and SP among SMEs. These findings are consistent with NRBV and DCT in suggesting that the sustainability benefits of BDA are contingent on complementary organizational capabilities such as circular economy practices, strategic agility, and learning orientation.

The second stream focuses on GI as a strategic resource. (Ramadana et al., 2025) show that GI improves sustainability performance among firms listed in the Sri Kehati Index, even though green innovation and slack resources do not always yield positive effects. (Indriastuti & Chariri, 2021) demonstrate that green and CSR investments enhance both financial and sustainability performance in Indonesian manufacturing firms, while (Nunik Nurmalasari & Sri Dwi Kania, 2024) find that GI improves financial but not sustainability performance in a small panel of manufacturing firms. (Ye & Dela, 2023) document that GI in foreign chemical companies operating in Indonesia increases SP with corporate social responsibility as a mediator. These divergent results indicate that GI does not automatically translate into SP; its effectiveness appears to depend on context, scale, implementation quality, and complementary capabilities, reinforcing NRBV's emphasis on capability development and DCT's focus on resource orchestration.

The third-stream addresses leadership and sustainability outcomes. Show that GTL, green HRM, and green innovation increase sustainable business performance, moderated by perceived organizational support. (Bhatti et al., 2023) find that GTL and green intellectual capital improve SP through green capabilities, especially when top management commitment is high. (Purwaningsih et al., 2023) provide evidence from Indonesia that GTL has a strong positive impact on corporate sustainable performance, while (A. N. Khan et al., 2024) highlight the role of green knowledge management and AI-enabled green human capital in promoting green technology innovation and SP. These studies are in line with TLT and DCT, suggesting that leadership and human capital mechanisms are critical for converting technology and investment into sustainability outcomes, and that GTL may operate simultaneously as an independent performance determinant and as a situational element that governs how organizational assets translate into measurable outcomes.

Methodologically, prior research relies heavily on cross-sectional survey designs, structural equation modeling, and single-country samples, often focused on manufacturing or construction sectors (Alyahya et al., 2023; Bhatti et al., 2023). Control variables such as firm size, profitability, leverage, and industry characteristics frequently show significant effects, and more recent works introduce green knowledge management and green talent management as additional controls, recognizing the role of human and intellectual capital (A. N. Khan et al., 2024; Umair et al., 2024). However, the combined effect of BDA and GI on SP under different leadership conditions remains underexplored, particularly using multi-year panel data and content analysis–based measures in an emerging-market setting such as Indonesia.

Previous research has generally focused on either BDA or GI, or on the direct effects of GTL on SP. However, research that attempts to investigate the joint influence of BDA and GI on SP and the moderating role of GTL within this relationship is still limited, especially in the context of Indonesian listed non-financial companies (Indriastuti & Chariri, 2021; Nunik Nurmalasari & Sri Dwi Kania, 2024; Sangpetch & Ueasangkomsate, 2023). Therefore, the current investigation formulates and statistically validates a holistic framework that concurrently embeds BDA, GI, and GTL to account for variations in SP. By grounding the model in NRBV, DCT, and TLT and validating it with panel data from Indonesian listed firms, this research addresses unresolved contradictions in prior findings and clarifies the boundary conditions under which digital and green resources, orchestrated by leadership, translate into superior sustainable performance.

The Influence of Big Data Analytics on Sustainable Performance

NRBV suggests that firms that develop capabilities for pollution prevention and resource optimization can achieve superior environmental and economic performance (Hart, 1995). BDA facilitates these organizational competencies through continuous surveillance systems, anticipatory analytical models, and the streamlining of material consumption and pollutant outputs. Empirical findings indicate that BDA can enhance SP, either directly or indirectly, through circular economy practices, supply chain flexibility, strategic agility, and green innovation (Alyahya et al., 2023; Sangpetch & Ueasangkomsate, 2023). Grounded in these theoretical and empirical considerations, the initial hypothesis is stated as:
H1: *Big Data Analytics has a positive effect on Sustainable Performance.*

The Influence of Green Investment on Sustainable Performance

Within the NRBV framework, GI is a strategic resource that supports sustainable development by financing clean technologies, eco-innovation, and environmental management systems (Hart & Dowell, 2011). Prior studies generally find that GI is associated with better sustainability outcomes, although the strength and significance of the relationship vary across samples and performance dimensions (Ramadana et al., 2025; Ye & Dela, 2023). Despite some inconsistent evidence, the dominant expectation is that firms that allocate more financial resources to green projects are better positioned to improve their environmental, social, and economic performance. Accordingly, the second proposition is advanced as:
H2: *Green Investment has a positive effect on Sustainable Performance.*

The Moderating Role of Green Transformational Leadership

Green Transformational Leadership Moderates Big Data Analytics → Sustainable Performance

DCT emphasizes that leadership is central to sensing, seizing, and transforming resources into competitive advantages (Teece, 2007). GTL, as a specific manifestation of transformational leadership in environmental contexts, is expected to strengthen the link between BDA and SP by ensuring that analytical insights inform strategic decisions and operational practices. Empirical studies show that GTL enhances the effectiveness of technological and environmental capabilities in improving SP through mechanisms such as capability development, organizational support, and green culture formation (Bhatti et al., 2023). Thus, firms with stronger GTL are likely to derive greater sustainability benefits from BDA than those with weaker GTL. The third hypothesis is stated as:
H3: *Green Transformational Leadership positively strengthens the influence of Big Data Analytics on sustainability outcomes.*

Green Transformational Leadership Moderates Green Investment → Sustainable Performance

NRBV and DCT jointly suggest that financial investments in environmental initiatives must be supported by organizational capabilities and leadership to be effective. GTL aligns GI decisions with a clear sustainability vision, mobilizes support across organizational levels, and monitors implementation outcomes. Evidence indicates that GTL can shape how environmental investments and initiatives translate into SP, amplifying their impact when leadership is strong (Aulia & Nawangsari, 2023; Purwaningsih et al., 2023). Accordingly, the fourth hypothesis is formulated as:

***H4:** Green Transformational Leadership positively strengthens the influence of Green Investment on sustainability outcomes*.

Conceptual Framework

Drawing upon the preceding theoretical grounding and hypothesis construction, the analytical framework of this investigation weaves together three principal associations. Foremost, BDA and GI are conceptualized as pivotal organizational assets that exert immediate effects on sustainability outcomes. Drawing on NRBV, firms that effectively deploy technological capabilities (BDA) and financial resources (GI) can achieve pollution prevention, resource optimization, and sustainable development, thereby enhancing their economic, environmental, and social outcomes. Second, GTL is conceptualized as both a direct predictor and a moderating mechanism. As a direct predictor, GTL shapes organizational culture, employee motivation, and strategic priorities aligned with sustainability objectives. As a moderator, GTL amplifies the effectiveness of BDA and GI by ensuring that data-driven insights are translated into concrete initiatives and that green investments are strategically selected, implemented, and monitored. Third, the framework incorporates GKM and GTM as covariates to accommodate the contribution of human capital and knowledge-based assets. These supplementary variables permit the disentanglement of the distinctive impacts of the core constructs on sustainability outcomes, thereby diminishing the likelihood of specification error from excluded variables and reinforcing the inferential robustness of the results.

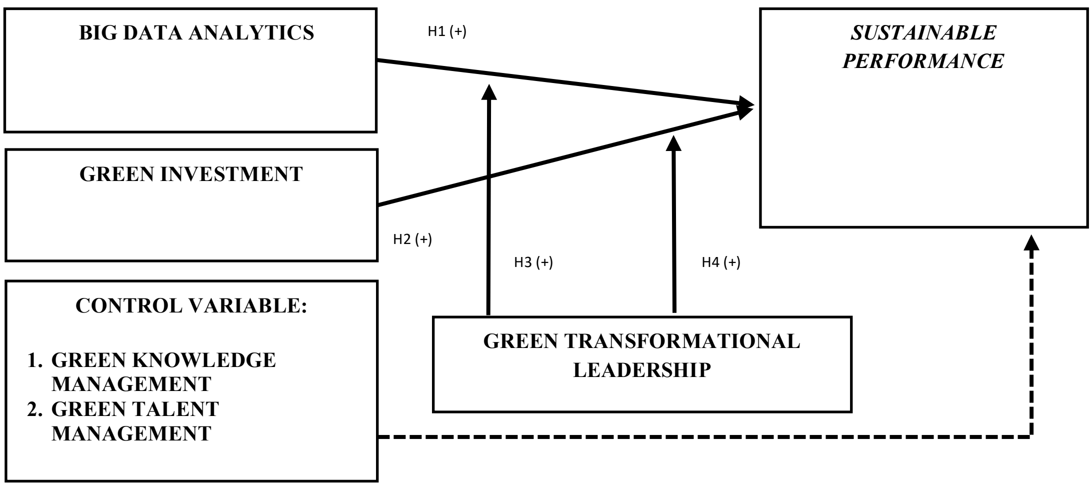

Figure 1. Conceptual Framework
Source: data processed by the author (2025)

3. Methods

Research Design

This study employs an explanatory quantitative approach using unbalanced panel data of non-financial firms listed on the Indonesia Stock Exchange (IDX) over the 2023–2024 period. The selection of this two-year period is grounded in the increasing standardization and availability of sustainability disclosures following recent regulatory strengthening in Indonesia. Although relatively short, the panel structure remains suitable for examining causal relationships by leveraging cross-sectional variation, which is particularly relevant in emerging market contexts where inter-firm differences are substantial.

Population, Sample, and Sampling Procedure

The target population encompasses every non-financial corporation registered on the IDX throughout 2023–2024. The selection of non-financial entities is justified by the fact that their primary operations entail physical manufacturing activities, material consumption, and ecological footprints that bear direct relevance to SP assessment. The population covers ten IDX sectors: Energy, Basic Materials, Industrials, Consumer Non-Cyclicals, Consumer Cyclicals, Healthcare, Technology, Infrastructure, Transportation & Logistics, and Property & Real Estate. The financial sector is excluded due to different regulatory regimes and performance characteristics (Ramadana et al., 2025).

A purposive sampling technique is applied (Etikan, 2016) with the following criteria. Inclusion criteria: (1) non-financial firms continuously listed on IDX during 2023–2024; (2) availability of complete annual and/or sustainability reports; (3) engagement in production activities (e.g., raw material transformation, productive fixed assets, tangible output, and inventory); and (4) complete data for all research variables. Exclusion criteria: (1) pure service and trading firms without production operations; (2) firms reporting consecutive losses in both years; (3) companies under delisting, suspension, or restructuring; and (4) financial statements not presented in Indonesian Rupiah.

Applying these criteria yields 775 firm-year observations (356 firms in 2023 and 419 firms in 2024). Outlier detection using the interquartile range (IQR) method leads to the removal of 34 extreme observations (Hair et al., 2019), yielding an ultimate analytical dataset comprising 741 firm-year data points. The sufficiency of the sample size is evaluated following the criterion established by (Green, 1991). With seven predictors in the moderated regression model, the minimum required sample is 106 observations. The final sample of 741 observations comfortably exceeds this threshold, providing sufficient statistical power for detecting moderate effects at $\alpha = 0.05$(Cohen et al., 2013).

Data Sources, Measurement, and Index Construction

The investigation depends entirely on archival data derived from two documentary sources: (1) annual corporate reports (laporan tahunan) encompassing governance arrangements, strategic direction, and financial performance data; and (2) sustainability reports (laporan keberlanjutan) that reveal environmental stewardship, social responsibility, and governance implementation. Documents are obtained from the official IDX portal and company websites to ensure authenticity and comparability (Beattie et al., 2004; Bryman, 2015).

Every construct is operationalized through content analysis methodology, which permits the structured numerical transformation of qualitative textual disclosures (Krippendorff, 2019). A coding framework adapted from (Siregar et al., 2025) for IDX-listed firms is applied. Each indicator for BDA, GI, SP, GTL, Green Knowledge Management (GKM), and Green Talent Management (GTM) is scored on a four-point scale: 0 = no disclosure; 1 =

narrative disclosure only; 2 = narrative plus quantitative information; 3 = comprehensive disclosure including narrative, quantitative, and visual or tabular representation.
For each construct j, a disclosure index is computed as:

$$\text{Index}_j = \frac{\sum_{i=1}^{n_j} \text{Score}_{ij}}{n_j \times 3} \times 100\%$$

where n_j denotes the number of indicators for construct j. This procedure yields indices ranging from 0% to 100%, with higher scores indicating more comprehensive disclosures (Hossain et al., 2006).

The operational definitions, dimensions, and specific items used for measurement are detailed in Table 1 below.

Table 1. Operational Definitions and Measurement

Variable	Dimension	Items	Source
Sustainable Performance (SP)	Economic performance; Environmental performance; Social performance.	13 Items	(N. U. Khan et al., 2021)
Big Data Analytics Capability (BDA)	Analytics tools & algorithms; Relationship discovery; Predictive analytics; New correlation & trend spotting; Analytics staff skills.	5 Items	(Hao et al., 2019)
Green Investment (GI)	Environmental protection consideration; Routine practice; Responsibility to society; Financial attractiveness; Cost-driven reduction.	5 Items	(Zhang & Berhe, 2022)
Green Talent Management (GTM)	Employee support & well-being; Green training; Autonomy in green tasks; Green performance appraisal; Governance in green initiatives; Organizational support.	14 Items	(Al-Romeedy & Alharethi, 2024)

Source: adapted from various journals

To verify the dependability of the coding procedure, two autonomous evaluators independently analyzed a randomly selected subset of 75 reports (roughly 10% of the total dataset). The degree of inter-rater consistency was measured using Cohen's Kappa coefficient, producing a value of $\kappa = 0.847$, signifying a high level of concordance (Landis & Koch, 1977). Discrepancies are resolved through discussion, and the agreed coding protocol is then applied to the full sample.

Research Model and Data Analysis Techniques

Statistical processing is performed using STATA 19.5, which offers an extensive suite of procedures for longitudinal data modeling and resilient statistical inference (Cameron & Trivedi, 2022). First, summary statistics encompassing the arithmetic mean, median value, standard deviation, minimum, and maximum are generated for every variable. Pearson product-moment correlation coefficients are subsequently calculated to assess pairwise associations and to conduct a preliminary evaluation of potential collinearity issues. Variance inflation factors (VIF) are inspected to confirm that multicollinearity remains within acceptable thresholds (Hair et al., 2019).

Panel model selection follows a standard sequence of tests (Baltagi, 2021; Wooldridge, 2018): the Chow test is utilized to adjudicate between pooled OLS and fixed effects (FE) specifications, the Breusch–Pagan Lagrange Multiplier (LM) test differentiates between pooled OLS and random effects (RE) approaches, and the Hausman specification test discriminates between FE and RE estimators. The preferred model is chosen based on these diagnostics.

Classical assumptions are examined through heteroskedasticity and serial correlation tests. The modified Wald statistic (under FE) and the Breusch–Pagan/Cook–Weisberg diagnostic (under RE) are deployed to identify non-constant error variance (White, 1980), whereas the Wooldridge procedure is implemented to evaluate serial dependence in longitudinal data (Drukker, 2003). Upon identification of violated assumptions, heteroskedasticity-consistent standard errors grouped at the corporate level are utilized to simultaneously correct for unequal variance and intra-firm temporal dependence (Petersen, 2009).

The proposed hypotheses were assessed through moderated hierarchical regression, drawing upon the analytical architecture prescribed by (Baron & Kenny, 1986) and (Hayes, 2018). The regression model estimates the effects of Big Data Analytics (BDA) and Green Innovation (GI) on Sustainable Performance (SP), while examining the moderating role of Green Transformational Leadership (GTL) and controlling for GKM and GTM. The regression equation is expressed as follows:

$$SP_{it} = \beta_0 + \beta_1\ BDA_{it} + \beta_2\ GI_{it} + \beta_3\ GTL_{it} + \beta_4\ (BDA*GTL)_{it} + \beta_5\ (GI*GTL)_{it} + \beta_6\ GKMit + \beta_7\ GTM_{it} + \varepsilon_{it}$$

To alleviate potential collinearity complications stemming from the multiplicative terms, all continuous predictor variables underwent mean-centering transformation before calculation (Aiken & West, 1991). The significance of the interaction coefficients (β4 and β5) is used to evaluate the presence and strength of the moderation effects (Cohen et al., 2013).

4. Result and Discussion

Descriptive Statistics

The definitive analytical dataset comprises 741 firm-year data points following the exclusion of 34 extreme values from the original 775 observations through application of the interquartile range (IQR) technique. Of these, 342 observations (46.15%) are from fiscal year 2023 and 399 observations (53.85%) from 2024. This pattern indicates increasing availability and completeness of sustainability-related disclosures among Indonesian listed companies, in line with strengthened regulatory requirements and stakeholder pressure for transparency (Siregar et al., 2025).

Table 2 displays the summary statistics for every research construct, incorporating indicators of central location and variability.

Table 2. Descriptive Statistics of Research Variables

Variable	N	Mean	Median	Std. Dev.	Min	Max
BDA	741	42.667	40.000	18.520	6.667	86.667
GI	741	38.940	36.667	16.780	0.000	80.000
GTL	741	35.820	33.333	17.410	0.000	83.333
SP	741	41.250	38.462	19.860	2.564	87.179
GKM	741	33.470	30.000	15.920	0.000	73.333
GTM	741	29.180	26.190	14.250	0.000	69.048

Notes: BDA = Big Data Analytics; GI = Green Investment; GTL = Green Transformational Leadership; SP = Sustainable Performance; GKM = Green Knowledge Management; GTM = Green Talent Management. All variables measured as disclosure index percentages (0-100%).
Source: data processed by the author (2025)

The descriptive statistics indicate that Big Data Analytics (BDA) has the highest mean disclosure index (42.67%), suggesting relatively more advanced adoption of analytics capabilities compared to other sustainability constructs. However, the wide standard deviation (18.52) and range (6.67%–86.67%) point to substantial heterogeneity across firms. Green Investment (GI) has a mean of 38.94% and median of 36.67%, with a minimum of 0.00%, showing that some firms provide no information on green investment at all, while others report moderate activity.

Green Transformational Leadership (GTL) records the lowest mean among the three main predictors (35.82%), indicating that explicit disclosure of sustainability-oriented leadership practices is still limited. The range from 0.00% to 83.33% reflects wide variation in how firms communicate their leadership's environmental commitment. Sustainable Performance (SP) has a mean of 41.25% and median of 38.46%, implying that most firms are at a moderate sustainability level. Meanwhile, the control variables, Green Knowledge Management (GKM) and Green Talent Management (GTM), have means of 33.47% and 29.18% respectively, suggesting that systematic environmental knowledge processes and green-oriented talent practices remain relatively nascent.

Table 5 shows that the dispersion measure for each variable falls below its corresponding central tendency value (Std Dev < Mean). To illustrate, BDA records an average of 42.67 paired with a dispersion of 18.52, while SP registers a mean value of 41.25 accompanied by a standard deviation of 19.86, and so forth. This pattern indicates that the distribution of variables is relatively homogeneous, suggesting that the data come from a population with similar characteristics (Hair et al., 2019). The relatively low dispersion strengthens the representativeness of the sample for the target population of Indonesian non-financial listed companies.

Correlation Analysis

Pearson product-moment correlation coefficients were calculated to explore the pairwise associations across all study constructs. Table 3 presents the correlation matrix with significance levels.

Table 3. Pearson Correlation Matrix

	BDA	**GI**	**GTL**	**SP**	**GKM**	**GTM**
BDA	1.000					
GI	0.428	1.000				
GTL	0.391	0.467	1.000			
SP	0.523	0.486	0.412	1.000		
GKM	0.358	0.321	0.389	0.367	1.000	
GTM	0.312	0.296	0.434	0.341	0.578	1.000

Source: data processed by the author (2025)

The correlation matrix demonstrates that each of the three predictor variables BDA, GI, and GTL displays favorable and statistically meaningful associations with Sustainable Performance. BDA shows the strongest correlation with SP ($r = 0.523$, $p < 0.01$), followed by GI ($r = 0.486$, $p < 0.01$) and GTL ($r = 0.412$, $p < 0.01$). These bivariate associations provide preliminary support for the hypothesized direct effects. The correlation results are consistent with the regression findings reported in Table 11, where both BDA ($\beta = 0.261$, $p < 0.01$) and GI ($\beta = 0.289$, $p < 0.01$) demonstrate significant positive effects on SP in the multivariate model.

However, the correlation coefficients are higher than the standardized regression coefficients, which is expected when controlling for other predictors and moderating effects.

Regarding the relationships among independent and control variables, correlations range from 0.296 to 0.578. The highest value (r = 0.578) occurs between the control variables GKM and GTM. Crucially, none of the correlations exceed the threshold of 0.80, indicating that multicollinearity is unlikely to pose serious problems in the subsequent regression analysis (Hair et al., 2019).

Panel Data Diagnostic Test Results

Given the panel data structure combining cross-sectional and time-series dimensions, systematic diagnostic tests were conducted to determine the appropriate estimation model and verify regression assumptions.

Table 4. Panel Data Model Selection and Assumption Diagnostic Test Results

Test	Purpose/ Comparison	Statistic	p-value	Conclusion
Chow Test (F-test)	Pooled OLS vs. Fixed Effects	$F(355, 378) = 1.247$	0.089	Fail to reject H_0; Pooled OLS adequate
Hausman Test	Fixed Effects vs. Random Effects	$\chi^2(7) = 9.834$	0.198	Fail to reject H_0; Random Effects preferred
Breusch-Pagan LM Test	Pooled OLS vs. Random Effects	$\chi^2(1) = 2.156$	0.142	Fail to reject H_0; Pooled OLS adequate
Modified Wald Test	Groupwise Heteroskedasticity	$\chi^2(356) = 398.742$	0.063	No significant heteroskedasticity
Wooldridge Test	Serial Correlation in Panel	$F(1, 355) = 2.418$	0.121	No first-order autocorrelation

Source: Data processed by the author (2025)

The outcomes of the estimation approach diagnostics uniformly support the adoption of the Pooled Ordinary Least Squares (OLS) specification. The Chow test yielded an F-statistic of 1.247 with a p-value of 0.089, which fails to reject the null hypothesis at the 5% significance level, suggesting that the Fixed Effects model provides no significant improvement over Pooled OLS. Similarly, the Breusch-Pagan Lagrange Multiplier (LM) test resulted in a Chi-square statistic of 2.156 ($p = 0.142$), indicating that the variation attributable to random heterogeneity does not materially deviate from zero, thereby confirming the appropriateness of the Pooled OLS estimator. While the Hausman test ($\chi^2 = 9.834$, $p = 0.198$) did not reject the null hypothesis (favoring Random Effects over Fixed Effects), the insignificant result of the LM test serves as the primary determinant for retaining the Pooled OLS approach. Taken together, these results support the use of pooled OLS as an efficient and appropriate approach for this relatively short panel dominated by cross-sectional variation (Baltagi, 2021; Wooldridge, 2018).

Following the model selection, additional diagnostic tests were performed to validate the assumptions of the Pooled OLS estimator. The Modified Wald diagnostic for group-level heterogeneous variance generated a Chi-square value of 398.742 with an associated probability of 0.063. Given that this figure surpasses the conventional 0.05 significance boundary, the assumption of uniform error variance across cross-sectional units cannot be dismissed, indicating that the error variances are sufficiently constant across cross-sectional units. Furthermore, the Wooldridge diagnostic for serial dependence produced an F-value of 2.418 ($p = 0.121$), establishing that no first-order temporal correlation exists among the residual terms.

The study propositions were evaluated through a stepwise moderated regression procedure; the outcomes are consolidated in the accompanying table. These results indicate no serious groupwise heteroskedasticity or first-order autocorrelation in the error terms (Drukker, 2003; White, 1980), ensuring the validity of the regression estimates.

Hypothesis Testing Results

The study propositions were evaluated through a stepwise moderated regression procedure; the outcomes are consolidated in the accompanying table.

Table 5. Moderated Regression Analysis Results

$SP_{it} = 7.894 + 0.261\ BDA_{it} + 0.289\ GI_{it} + 0.142\ GTL_{it} + 0.187\ (BDAxGTL)_{it} + 0.160\ (GIxGTL)_{it} + 0.091\ GKM_{it} + 0.071\ GTM_{it} + e_{it}$

Variable	Prediction	Coefficient	Std. Error	t-stat	Sig.	VIF	Tolerance
Constant		7.894	2.087	3.78	0.000***	-	-
BDA	(+)	0.261	0.051	5.12	0.000***	1.847	0.541
GI	(+)	0.289	0.045	6.42	0.000***	1.923	0.520
GTL	(+)	0.142	0.040	3.55	0.000***	2.156	0.464
BDA × GTL	(+)	0.187	0.058	3.22	0.001***	3.125	0.320
GI × GTL	(+)	0.160	0.064	2.50	0.013**	3.247	0.308
GKM		0.091	0.037	2.46	0.014**	2.478	0.404
GTM		0.071	0.041	1.73	0.083*	2.634	0.380
R^2		0.503					
Adj. R^2		0.498					
F-statistic		105.267			0.000***		
N		741					

Notes: ***p < 0.01, **p < 0.05, *p < 0.10;

Source: data processed by the author (2025)

The estimated model exhibits considerable explanatory capacity, as substantiated by the overall model adequacy indicators. As shown in the table, the Adjusted R-squared value is 0.498, indicating that the independent variables (Big Data Analytics, Green Investment, and Green Transformational Leadership) and their interaction terms, together with the control variables (Green Knowledge Management and Green Talent Management), explain approximately 49.8% of the variance in Sustainable Performance. The remaining 50.2% of the variance is explained by other factors not included in the model. Furthermore, the simultaneous significance test confirms the model's validity; the F-value equals 105.267 at a significance level of 0.000 ($p < 0.001$). This outcome reveals that the predictor variables collectively exert a meaningful influence on the criterion variable, verifying that the regression specification possesses statistical validity and suitability for forecasting Sustainable Performance.

Prior to examining the individual parameter estimates, foundational diagnostic assessments were performed to ascertain the reliability of the regression specification. First, regarding normality, the Shapiro-Wilk statistic (W = 0.988) alongside the Kolmogorov-Smirnov statistic (D = 0.029) both generate probability values exceeding 0.05, demonstrating that the error distributions conform to the normality requirement. Second, the collinearity diagnostic reveals that Variance Inflation Factor (VIF) scores across all constructs span from 1.847 to 3.247, remaining comfortably beneath the critical cutoff of 10, with corresponding tolerance figures ranging between 0.308 and 0.542, each surpassing the 0.10 minimum. These diagnostics validate that no concerning inter-predictor dependencies exist. Third, the heteroskedasticity assumption is met, as both the Breusch-Pagan test and the White test yield insignificant results ($p > 0.05$), indicating that the error variance is constant across observations. Finally, the Durbin-Watson coefficient registers at 1.987, approximating the ideal benchmark of 2.0, which signifies that the null premise of absent temporal dependence is upheld and the requirement of serially independent residuals is fulfilled.

The hypothesis testing for direct effects reveals significant findings based on the t-statistics and probability values. The first hypothesis (H1) receives empirical validation, given that the regression parameter for Big Data Analytics equals 0.261 at a significance threshold of $p < 0.01$; as this probability falls below the 0.05 benchmark, the null proposition is refuted, substantiating a meaningful favorable impact of Big Data Analytics on Sustainable Performance. Correspondingly, the second hypothesis (H2) gains empirical backing, with the Green Investment parameter registering 0.289 at a significance level of $p < 0.01$, evidencing a substantial favorable influence of Green Investment on Sustainable Performance. Regarding the control variables, Green Knowledge Management (GKM) shows a significant positive effect (coefficient = 0.091, $p < 0.05$), while Green Talent Management (GTM) shows a marginally significant positive effect (coefficient = 0.071, $p < 0.10$).

Further analysis of the interaction effects provides evidence for the moderating role of leadership. The third hypothesis (H3) is corroborated, as the multiplicative coefficient linking Big Data Analytics with Green Transformational Leadership amounts to 0.187 ($p < 0.01$); this favorable and statistically meaningful value signifies that Green Transformational Leadership amplifies the beneficial impact of Big Data Analytics on Sustainable Performance. The fourth hypothesis (H4) likewise receives support, as the interaction parameter between Green Investment and Green Transformational Leadership reaches 0.160 ($p < 0.05$). The favorable direction and statistical significance of this coefficient indicate that Green Transformational Leadership reinforces the advantageous influence of Green Investment on Sustainable Performance.

Discussion

The empirical outcomes holistically address the investigative questions and illuminate the combined mechanisms through which digital, financial, and leadership determinants collectively govern sustainability outcomes. The empirical results demonstrate that firms with higher levels of Big Data Analytics (BDA) and Green Investment (GI) achieve significantly better Sustainable Performance (SP). From a conceptual standpoint, these results are consistent with the Natural Resource-Based View, which highlights environmental capabilities and investments as strategic resources that can generate sustainable competitive advantage (Hart, 1995; Hart & Dowell, 2011). Specifically, BDA supports real-time environmental monitoring, predictive maintenance, and resource optimization, enabling more efficient and environmentally friendly operations (Halbusi et al., 2024). Meanwhile, GI reflects a tangible financial commitment to green projects, technologies, and infrastructure, which directly reduces environmental impact and enhances stakeholder trust (Indriastuti & Chariri, 2021a; Ye & Dela, 2023).

This positive relationship between BDA and SP aligns with recent studies showing that analytics can enhance triple-bottom-line performance through circular economy practices, strategic agility, and green innovation (Alshuaibi et al., 2024; Alyahya et al., 2023; Sangpetch & Ueasangkomsate, 2023). However, it contrasts with (Edwin Cheng et al., 2022), who reported only indirect effects. This divergence suggests that in the Indonesian context, regulatory pressure and disclosure requirements may create stronger direct links between analytics usage and sustainability outcomes. Similarly, the findings regarding GI are consistent with (Ramadana et al., 2025) and (Ye & Dela, 2023), who found that green investments improve sustainability performance. This differs from (Nunik Nurmalasari & Sri Dwi Kania, 2024), who did not detect a significant effect in a smaller, sector-specific sample. The broader cross-sector panel and content-analysis–based indices employed in this study likely capture more diverse and mature forms of green investment, thereby revealing stronger performance effects.

Extending beyond the immediate effects, the investigation demonstrates that Green Transformational Leadership (GTL) concurrently exercises a favorable influence on SP and intensifies the effectiveness of BDA and GI, revealing an essential quasi-moderating function. Dynamic Capabilities Theory provides a robust explanation for this mechanism; leaders with strong green transformational qualities help the firm sense sustainability-related opportunities and threats, seize them via appropriate digital and green investments, and transform routines to support sustainable business models (Teece, 2007). Furthermore, Transformational Leadership Theory explains the behavioural mechanisms through which these leaders inspire environmental vision, stimulate green innovation, and support employees in adopting pro-environmental behaviours (Bass & Riggio, 2006; Chang & Chen, 2012). Consequently, in firms with strong GTL, analytics-based insights are more likely to be translated into concrete sustainability initiatives, and green investments are prioritized and implemented more effectively.

The evidence regarding GTL extends previous research that has primarily examined its direct or mediating roles (Bhatti et al., 2023). By demonstrating that GTL amplifies the effectiveness of both BDA and GI, this study highlights leadership as a key contingency that can reconcile mixed findings in earlier studies on technology and investment. Without supportive leadership, even substantial analytics and green investment efforts may not translate fully into sustainable performance. In the Indonesian setting, the relatively modest average disclosure indices for all constructs indicate that a considerable proportion of corporations remain at nascent or transitional phases of sustainability adoption. However, the significant variation across firms suggests that a subset of companies is emerging as sustainability leaders by leveraging digital transformation, green finance, and transformational leadership in an integrated manner. Taken together, the findings underscore that achieving superior sustainable performance is not merely a function of how much firms invest in technology and green projects, but also how these resources are orchestrated and led. Integrating BDA, GI, and GTL into a coherent sustainability strategy appears crucial for Indonesian listed firms seeking to close the gap between sustainability commitments and realized outcomes.

The empirical findings confirm that Big Data Analytics (BDA) and Green Investment (GI) are positively associated with Sustainable Performance (SP), supporting the core propositions of the Natural Resource-Based View and Dynamic Capabilities Theory. Firms that invest in data-driven capabilities and environmental initiatives appear better positioned to improve resource efficiency, reduce environmental impact, and enhance overall sustainability outcomes. The significant moderating role of Green Transformational Leadership (GTL) further reinforces the argument that leadership is a critical mechanism in translating strategic resources into tangible performance gains.

Despite these consistent results, a more critical interpretation is necessary. One important consideration is that the study relies on disclosure-based measures, which may capture symbolic rather than substantive sustainability practices. Firms may strategically disclose BDA capabilities and green investments to comply with regulatory expectations or enhance legitimacy without fully implementing these initiatives in operational processes. This raises the possibility that part of the observed positive relationship reflects signaling effects rather than actual performance improvements.

In addition, institutional factors in Indonesia may shape the effectiveness of these relationships. Regulatory pressure, stakeholder expectations, and varying levels of corporate governance maturity could influence how firms adopt and report sustainability practices. The relatively moderate average disclosure scores across all variables suggest that many firms are still at an early or transitional stage of sustainability integration. This indicates that, while leading firms are able to leverage BDA, GI, and GTL effectively, a substantial proportion of companies may lack the internal capabilities or organizational readiness to do so.

The role of GTL as a quasi-moderator provides an important insight but also raises practical concerns. Firms with weaker leadership capabilities may struggle to convert digital and financial investments into meaningful sustainability outcomes. Without strong leadership commitment, BDA initiatives may remain underutilized, and green investments may be implemented inefficiently or disconnected from core strategy. This highlights the need for firms to prioritize leadership development alongside technological and financial investments.

Overall, the findings demonstrate that achieving sustainable performance is not solely dependent on the availability of resources but also on how effectively these resources are orchestrated within organizational and institutional contexts. By incorporating both supportive evidence and critical reflection, this study provides a more nuanced understanding of sustainability transformation in emerging markets.

5. Conclusion

This study examines the effects of Big Data Analytics (BDA) and Green Investment (GI) on Sustainable Performance (SP) among Indonesian non-financial listed firms during the 2023–2024 period, while also evaluating the moderating role of Green Transformational Leadership (GTL). Based on 741 firm-year observations analyzed using panel regression and disclosure-based indices, the findings indicate that both BDA and GI have significant positive effects on sustainable performance, confirming that digital capabilities and environmental investments are essential resources in improving sustainability outcomes in emerging markets. Among the two, green investment demonstrates a relatively stronger direct influence, suggesting that financial commitment to environmental initiatives plays a central role in driving sustainability performance. Furthermore, Green Transformational Leadership is found to perform a dual function, both directly enhancing sustainable performance and strengthening the effects of BDA and GI, thereby supporting its classification as a quasi-moderator. This implies that leadership not only acts as an independent driver but also amplifies the effectiveness of technological and financial resources. In addition, Green Knowledge Management and Green Talent Management contribute positively, although their effects are comparatively smaller, indicating that leadership, technology, and investment remain the dominant factors in the Indonesian context.

Despite these contributions, several limitations should be acknowledged. The relatively short observation period may limit the ability to capture long-term sustainability dynamics, while the reliance on disclosure-based measures raises the possibility that the results reflect symbolic reporting rather than fully implemented practices. The use of corporate reports as the primary data source may also introduce self-reporting bias. Moreover, the exclusion of financial firms and loss-making companies may constrain the generalizability of the findings across sectors. Future research is therefore encouraged to extend the observation period, incorporate cross-country comparisons, and apply alternative methodological approaches such as longitudinal causal models or mixed methods. Further investigation into governance quality, institutional pressures, and behavioral factors would also provide a deeper understanding of how sustainability performance is achieved in emerging market settings.

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