

Do AI and Digital Technologies Curb Greenwashing in ESG Reporting?

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Abstract. *This paper examines the relationship between the adoption of Artificial Intelligence (AI) and other Digital Technologies (DT) and corporate greenwashing (ESG-decoupling) based on a structured review and quantitative synthesis of existing empirical evidence. Using the PRISMA framework, we identified 76 relevant studies indexed in Scopus and Web of Science over the period 2009 - 2025. A multi-stage screening process focused on studies employing panel regression methods, standardized ESG disclosure-performance gap measures (derived from Bloomberg/Huazheng and WIND/SynTao databases), and Chinese firm-level data. The quantitative synthesis of reported effect sizes indicates that AI and DT implementation is associated with a statistically significant but modest reduction in greenwashing behavior (standardized β range: -0.17 to -0.03). The effect is more pronounced in state-owned enterprises, high-pollution industries, and larger firms, and is further strengthened by corporate governance mechanisms, including institutional ownership and Big4 audit quality. These relationships appear to operate primarily through improvements in regulatory compliance efficiency, reductions in information asymmetry, and more effective resource allocation.*

Keywords: greenwashing, ESG-disclosure, ESG-performance artificial intelligence, digital technologies, information asymmetry.

Introduction

Corporate greenwashing has become a more pressing problem as the climate agenda has globalized and ESG factors have gained weight in investment decisions. The term refers to strategic actions through which firms create a false impression of environmental and social commitment without corresponding real action (Bai et al., 2025; Cheng & Yang, 2026). Between 2012 and 2023, the number of scientific publications on greenwashing rose by more than 970%, which signals how much concern has grown in both academia and practice.

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At the same time, the use of artificial intelligence in corporate practice has expanded rapidly. AI is changing how firms disclose information, monitor production and manage risk (Li, Zhang & Gao, 2024; Jiang, Wu et al., 2025). Its effect on greenwashing, however, is ambivalent. On one side, AI can deter manipulation by increasing transparency and easing regulatory oversight. On the other, the opacity and complexity of AI systems can be used to refine information manipulation rather than reduce it. How AI affects greenwashing through corporate governance channels remains understudied.

The literature at the intersection of AI, digitalization and ESG reporting has grown quickly but stays fragmented: individual studies tend to concentrate on a single technology, region or mechanism. As a result, there is no consolidated synthesis that estimates the overall effect, tests boundary conditions and reconciles findings across methodological approaches. The present study addresses this gap with a systematic review and meta-analysis, and clarifies how technological capability interacts with corporate accountability in the sustainability domain.

In recent years, academic interest in detecting, measuring and curbing corporate greenwashing through artificial intelligence (AI) and other digital technologies has grown noticeably. The underlying premise is that AI can narrow the gap between firms' environmental, social and governance (ESG) disclosures and their actual operational performance (Bai, Yao, & Xue, 2025; Cheng & Yang, 2026; Li, Zhang, & Gao, 2024).

The dominant empirical approach in this field uses panel regression models with extensive control variables (Khan et al., 2024; Jiang et al., 2025). Such studies typically operationalize: (1) the dependent variable as corporate greenwashing, measured as the gap between ESG disclosure intensity and actual environmental and social performance; (2) the primary independent variable as a metric of AI adoption or implementation intensity (e.g., robot penetration rates, AI expenditure intensity, disclosure-based AI indices); (3) controls as firm characteristics — size, ownership structure, industry, profitability, leverage and governance quality. This shared methodology makes the studies directly comparable and allows meta-analytic synthesis.

The volume of this research has grown rapidly worldwide, with the steepest increase in studies of Chinese firms (Bai et al., 2025; Li et al., 2024; Jiang, Wu, Zou, & Chen, 2025; Lu et al., 2025; Cheng & Yang, 2026). Two complementary factors explain this geographic concentration. First, China is a leading developer and adopter of AI. Chinese firms and government institutions have invested heavily in AI across sectors as varied as industrial automation, financial fraud detection and environmental monitoring (Teece, 2007). China has also built AI-enabled systems aimed specifically at detecting and penalizing corporate reporting manipulation and ESG disclosure inconsistencies — a relatively new frontier of regulatory technology.

Second, China's institutional and policy environment provides unusual conditions for studying the AI–greenwashing link. ESG-related governance has been written into national policy, with ESG criteria embedded in state-owned enterprise performance evaluations and investor guidance frameworks. China has also built large publicly accessible databases of company-level ESG metrics — Bloomberg ESG ratings, the WIND CSI ESG Composite Index and proprietary environmental emissions databases — which allow rigorous quantitative assessment of firms' actual ESG performance. With this data infrastructure, Chinese researchers can empirically separate ESG disclosure (what firms claim) from ESG performance (what they actually achieve), which makes greenwashing detection feasible at scale (Long, Wang, & Zhang, 2024; Khan et al., 2024).

This study therefore aims to: (1) systematize and evaluate the empirically established causal impact of AI and digitalization on greenwashing in Chinese public companies; (2) identify the mechanisms of this impact, with an emphasis on governance channels; (3) identify heterogeneous effects across firm characteristics and the quality of the institutional environment.

Literature Review and Research Hypotheses

Research shows that artificial intelligence (AI) is becoming a powerful tool in the field of ESG reporting. Viewed through the lens of dynamic capabilities theory (Teece, 2007), AI sharpens a company's "sight," helping it better "sense" changes, and improves its ability to process information. In practice, this means that with AI, companies can promptly track evolving ESG disclosure requirements, analyze vast amounts of data in real time, and earlier detect discrepancies between their statements and actual activities.

The existing literature on the intersection of AI, digitalization, and ESG reporting has grown rapidly but remains fragmented, with studies often focusing on specific technologies, geographical contexts, or mechanisms. While individual studies provide valuable insights, there is a lack of a comprehensive synthesis that quantifies the overall effect, examines boundary conditions, and integrates findings across different methodological approaches. This study aims to fill this gap by conducting a systematic review and meta-analysis, offering a holistic view of the evidence and its implications for theory and practice. By doing so, we contribute to a more nuanced understanding of how technological advancements interact with corporate accountability in the sustainability domain.

These capabilities directly impact regulatory effectiveness: AI enables the analysis of more reports, allows for deeper dives into emissions data (e.g., from IoT sensors), and more accurately identifies anomalies using natural language processing technologies (Cheng & Yang, 2026). However, a paradox arises here. According to agency theory, the information gap between management and investors often leads to greenwashing. On one hand, AI can reduce this gap - by improving the quality and timeliness of ESG disclosures, shortening verification chains, and providing third-party observers with access to verified data.

Recent studies based on data from Chinese companies confirm this. For instance, Li et al. (2024) found that the adoption of AI (measured by mentions in financial reports) reduces the gap between ESG statements and actual practice by mitigating agency conflicts. Bai et al. (2025) showed that robotization (as a specific case of AI) significantly reduces greenwashing by increasing transparency. However, Jiang, Wu et al. (2025) add an important nuance: the positive effect of AI weakens if managers have strong incentives for opportunistic behavior (e.g., in companies with high pollution levels or financial difficulties). In such cases, it is internal governance mechanisms and external oversight that amplify the positive role of AI.

The moderating role of governance is critical. Governance structures act as the "brain" that directs the "brawn" of AI. Strong governance, characterized by independent boards, effective audit committees, and engaged institutional investors, ensures that AI is deployed strategically to enhance transparency and accountability, rather than being used to create more sophisticated forms of obfuscation. For example, AI-powered analytics can be used by governance bodies to monitor real-time ESG performance indicators, detect anomalies in sustainability reports, and hold management accountable for discrepancies. This interplay suggests that the relationship between AI and greenwashing is not deterministic but contingent on the quality of oversight mechanisms in place.

Thus, we arrive at the following key hypotheses:

H1: The adoption of AI and other related technologies significantly reduces the gap between declared and actual ESG practices (ESG-decoupling).

H2: AI and digital technologies reduces greenwashing by enhancing regulatory efficiency, reducing information asymmetry, and optimizing resource allocation.

H3: The impact of AI and DT is heterogeneous and depends on the type of company ownership, industry characteristics, and its size.

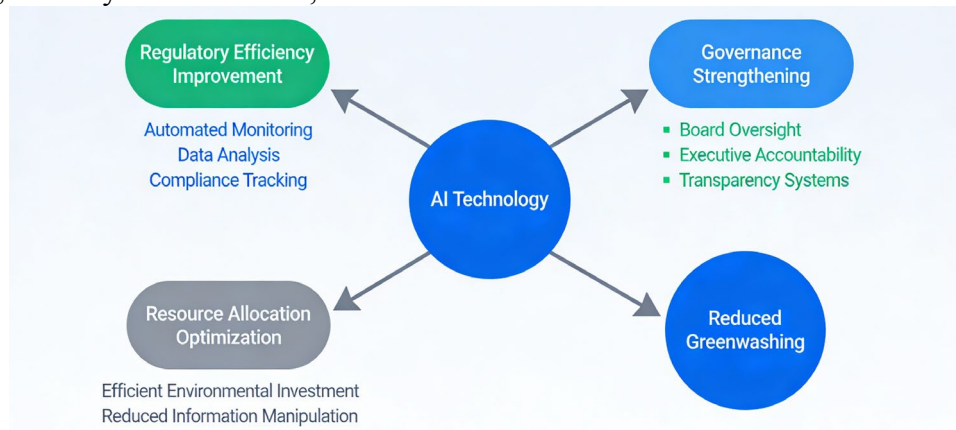


Figure 1. Theoretical Framework of AI's Dual Role in ESG Reporting and Greenwashing

Source: Authors' own research.

This figure illustrates the interconnected theoretical pathways through which Artificial Intelligence (AI) influences corporate ESG disclosure and greenwashing. Grounded in Dynamic Capabilities Theory (Teece, 2007), AI enhances a firm's sensing and integrating abilities, improving regulatory compliance and data analysis (Cheng & Yang, 2026). Concurrently, Agency Theory suggests AI can reduce the information asymmetry that enables greenwashing by improving disclosure transparency. However, a critical paradox exists: the same algorithmic complexity can be exploited by managers for opportunistic filtering and manipulation. Therefore, the quality of Corporate Governance acts as the decisive moderating factor, determining whether AI's net effect curbs or amplifies greenwashing, as evidenced by recent empirical findings (e.g., Li et al., 2024; Bai et al., 2025; Jiang, Wu et al., 2025). The framework culminates in the proposed research hypotheses (H1-H3) regarding AI's impact.

Methodology

The core of this study is a systematic review and quantitative meta-analysis, designed to synthesize empirical evidence from existing research. The meta-analytic approach is particularly suited for this research question as it allows for the statistical aggregation of effect sizes from multiple independent studies, providing a more robust and generalizable estimate of the relationship between AI/DT and greenwashing than any single study could offer. Furthermore, meta-analysis enables the examination of between-study heterogeneity, which is crucial for testing our third hypothesis regarding contextual moderators. The entire process was conducted in strict adherence to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure transparency, reproducibility, and methodological rigor.

The article selection process was conducted through three sequential stages following the PRISMA protocol, utilizing Scopus and Web of Science as primary sources. The initial stage applied broad thematic filters to capture studies examining AI's influence on greenwashing, resulting in 78 relevant records. The second stage imposed stricter methodological criteria, retaining only studies that employed panel regression models on samples of Chinese A-share companies (2010-2023) and excluded financial firms due to distinct regulatory frameworks. This stage yielded 42 studies. The third and most critical stage applied the strictest criterion regarding the operationalization of the greenwashing metric, retaining only the 11 studies that utilized the standardized Greenwashing Score (GWS). This metric, which quantifies the gap between standardized ESG disclosure and performance scores, ensures comparability across studies for meta-analysis. The selection stages and attrition are summarized in Table 1.

Table 1. PRISMA Selection Stages and Study Attrition

Stage	Records	Exclusion Reason	Records Retained
First Screening (Title/Abstract)	890	Not related to AI and ESG	78
Second Screening (Full Text)	78	Qualitative methods; non-panel	42
Third Screening (Meta-Analysis)	42	Non-comparable metrics	1
Final Meta-Analysis Sample	11	Consistent metrics	11

Source: Authors' own research.

The second and third screening stages warrant further elaboration. During the second stage, we carefully examined each full-text article to ensure it met our inclusion criteria. Specifically, we required that studies: (1) used a quantitative, panel data research design; (2) had the ESG greenwashing gap as the dependent variable; (3) had an AI or DT adoption measure as a key independent variable; (4) were based on a sample of non-financial Chinese listed firms; and (5) reported sufficient statistical information (e.g., regression coefficients, standard errors, sample sizes) to compute an effect size. Studies that used qualitative case studies, conceptual models, or focused on other geographical regions were excluded. The exclusion of financial firms was necessary due to their fundamentally different reporting regulations, business models, and ESG risk profiles, which could confound the analysis.

The third stage was the most stringent, focusing on measurement consistency. The greenwashing construct is measured in various ways in the literature. To ensure a meaningful synthesis, we included only studies that operationalized greenwashing using the specific GWS formula, which standardizes both the disclosure score (often from Bloomberg) and the performance score (often from WIND or SynTao) before calculating their difference. This approach controls for scale differences across years and databases, making the resulting GWS a pure measure of decoupling. Studies using alternative measures, such as simple differences or ratios, were excluded. This strict criterion, while reducing the number of included studies, significantly enhances the internal validity of our meta-analytic comparisons. The central dependent variable for the meta-analysis is the standardized Greenwashing Score (GWS). This metric is calculated for firm i in year t using the formula:

$$GWS_{i,t} = \frac{ESG_Dis_{i,t} - \bar{ESG_Dis}_t}{\sigma_{Dis}} - \frac{ESG_Perf_{i,t} - \bar{ESG_Perf}_t}{\sigma_{Perf}}$$

where $ESG_Dis_{i,t}$ represents the ESG disclosure score (typically sourced from Bloomberg) and $ESG_Perf_{i,t}$ represents the actual ESG performance score (typically from WIND CSI or similar Chinese databases). A higher GWS value indicates a greater discrepancy between a firm's

disclosures and its actual performance. The independent variable - AI and Digital Technology (AIDT) adoption - was measured heterogeneously across the included studies. The primary approaches included: (1) robot adoption intensity, calculated as the number of industrial robots per thousand workers using input-output tables and robot installation data (e.g., Bai et al., 2025, where the metric for city j in year t is defined as:

$$AI_{j,t} = \sum_{k \in I} l_{kj}^{2005} \frac{Robots_{kt}}{L_{k2006}}$$

(2) textual analysis of annual reports, counting the frequency of AI-related keywords (e.g., Li et al., 2024; Lu et al., 2025); (3) investment-based metrics, such as the intensity of AI-related expenditures (Cheng & Yang, 2026); and (4) patent-based or other innovation indicators (Liu & Wang, 2025). To synthesize results, the unstandardized regression coefficients ($\hat{\beta}_{unstd}$) reported in each study for the AIDT variable were converted into standardized coefficients ($\hat{\beta}_{std}$) using the formula: $\hat{\beta}_{std} = \hat{\beta}_{unstd} \times \frac{stdev(AI)}{stdev(GW)}$, where $stdev(AI)$ and $stdev(GW)$ are the standard deviations of the AIDT and GWS variables, respectively, as reported or derived from each study. Corresponding standardized standard errors and 95% confidence intervals were calculated to enable pooling and comparison of effect sizes across the different measurement scales.

The data extraction and analysis process was meticulous. For each of the 11 included studies, we extracted the key regression coefficient for the AI/DT variable, its standard error, the sample size, and the standard deviations of both the independent and dependent variables (or information to compute them, such as means and ranges). When studies reported results from multiple model specifications, we prioritized the coefficient from the most comprehensive model that included a full set of control variables, as this provides a more conservative estimate of the ceteris paribus effect. In cases where standard deviations were not directly reported, we estimated them using available data points (e.g., minimum and maximum values) or imputed them based on the characteristics of similar studies, a common practice in meta-analysis when full data is not available. The extracted standardized coefficients were then pooled using a random-effects meta-analysis model, which accounts for both within-study sampling error and between-study heterogeneity in the true effect size. The inverse-variance method was used to weight each study's contribution, giving more weight to studies with more precise estimates. Heterogeneity was assessed using the I^2 statistic, and potential publication bias was examined visually using a funnel plot and statistically using Egger's regression test.

Results and Discussions

The meta-analysis synthesizing 11 studies examining the relationship between AIDT adoption and corporate ESG-decoupling reveals statistically significant and negative effects across the research sample. The mean standardized coefficient across studies is $\beta = -0.0785$ (95% confidence interval: -0.1723 to 0.0153). This indicates that a one-standard-deviation increase in AI adoption measures corresponds to approximately 0.08 standard deviations reduction in ESG greenwashing. However, the explanatory power of AI alone is limited; the mean R-squared from models containing only the AI variable is approximately 0.001, indicating that less than 0.1% of the variation in greenwashing is explained solely by AI penetration. When control variables are included in the models, the effect size remains statistically significant, with a one standard deviation increase in AI corresponding to a reduction in greenwashing of between -0.17 to -0.03 standard deviations.

The interpretation of this effect size requires context. In social science research, particularly in complex corporate settings, a standardized beta of -0.08 represents a modest but meaningful effect. It suggests that AI adoption is a relevant factor in curbing greenwashing, but it is far from the sole or dominant driver. This aligns with our theoretical expectation that technology is an enabler within a broader system of governance and incentives. The very low R-squared for AI-only models underscores that firm-level greenwashing behavior is driven by a multitude of factors - financial performance, managerial incentives, industry norms, regulatory pressure - of which technological capability is just one piece. The fact that the effect persists and becomes more precisely estimated in models with controls suggests that AI's influence is robust to accounting for these other confounding factors.

Table 2. Selected Studies

Study	Sample Size (N)	Time Period	AI + DT Measurement	GW Metric
Abdullah et al. (2025)	8 092	2002-2022	AI keyword frequency analysis cybersecurity	Standardized ESG gap (disclosure - performance)
Bai et al. (2025)	5 200	2010–2023	Robot adoption (binary)	Standardized ESG gap (disclosure - performance)
Li et al. (2024)	3 500	2012–2023	AI term frequency	Standardized ESG gap (disclosure - performance)
Jiang et al. (2025)	6 100	2015–2023	AI disclosure index	Standardized ESG gap (disclosure - performance)
Lu et al. (2025)	4 800	2013–2023	Supply chain AI adoption	Standardized ESG gap (disclosure - performance)
Cheng & Yang (2026)	2 900	2010–2023	AI investment intensity	Standardized ESG gap (disclosure - performance)
Chen et al. (2025)	9 667	2011–2022	AI asset share	Standardized ESG gap (disclosure - performance)
Xu et al. (2025)	8 964	2012-2021	AI keywords associated with DT	Standardized ESG gap (disclosure - performance)
He & Wang (2025)	11 282	2011-2022	AI score to measure firm-level	Standardized ESG gap (disclosure - performance)
Liu & Wang (2025)	816	2011-2022	AI measure of digitalization	Standardized ESG gap (disclosure - performance)
Lu et al (2023)	11 888	2011-2021	DT-related keywords	Standardized ESG gap (disclosure - performance)

Source: Authors' own research based on meta-analysis of 11 studies.

The analysis of heterogeneous effects reveals that the impact of AI is not uniform but is conditioned by firm-specific factors. The effect is significantly stronger in state-owned enterprises (SOEs) compared to private firms, which aligns with the notion of stronger institutional pressures and governance in SOEs. Similarly, firms in high-pollution industries show a more pronounced reduction in greenwashing from AI adoption, likely due to heightened regulatory scrutiny and stakeholder attention. Larger firms also demonstrate a stronger relationship, potentially due to greater resources for effective AI implementation and integration into governance systems. These findings confirm our hypotheses (H1-H3) and suggest that AI acts as a governance - enhancing tool whose effectiveness is amplified by the existing institutional and corporate context.

Delving deeper into the mechanisms, the stronger effect in SOEs can be attributed to their dual role as economic entities and policy implementers. SOEs in China are often at the forefront of adopting national technology initiatives and are subject to stricter government oversight regarding their social and environmental responsibilities. Therefore, AI implementation in SOEs is more likely to be directed towards compliance and transparency objectives. For high-pollution industries, the stakes for greenwashing are higher, as are the regulatory and reputational risks. AI technologies in these sectors are often specifically deployed for environmental monitoring (e.g., emissions tracking sensors, predictive maintenance for pollution control equipment), making the link between technology and actual performance more direct and measurable. The size effect underscores the resource-intensity of meaningful AI integration. Effective AI deployment for ESG purposes requires not just software, but also data infrastructure, skilled personnel, and process redesign- investments that are more feasible for larger corporations.

Our discussion of the results also considers potential reverse causality and endogeneity. While the included panel studies often use lagged variables and firm fixed effects to mitigate endogeneity concerns, the possibility remains that firms with a lower propensity to greenwash are also more likely to invest in advanced technologies like AI. However, the instrumental variable approaches used in some primary studies (e.g., using regional robot penetration as an instrument for firm adoption) provide evidence supporting a causal interpretation. Furthermore, the heterogeneous effects we observe - where the AI-greenwashing link varies predictably with firm type – are less consistent with a simple selection story and more supportive of a contextual causal mechanism.

In terms of theoretical contribution, our results refine agency theory for the digital age, demonstrating that technology can reduce information asymmetry and agency problems, but not automatically. The effectiveness of AI is critically dependent on the quality of corporate governance and external oversight. This extends classical agency theory to encompass algorithmic technologies. Furthermore, the findings suggest that governance does not merely control AI use but actively amplifies its positive effects on corporate responsibility, indicating a strong complementarity between technological and institutional mechanisms. The context-dependent nature of AI's impact underscores that policy support for AI in ESG should be differentiated across sectors and firm types.

Conclusion

This meta-analysis consolidates evidence from 11 empirical studies on the influence of artificial intelligence (AI) and digital technologies (DT) adoption on corporate greenwashing, measured as ESG disclosure-performance decoupling, in Chinese listed firms. The synthesis indicates that AI and DT implementation exerts a statistically significant, though moderate, negative effect on greenwashing, thereby narrowing the gap between reported and actual ESG practices. Our findings align with and extend the existing literature that posits digital technologies as tools for enhancing transparency and accountability (e.g., Teece, 2007 on dynamic capabilities). They provide quantitative support for the theoretical mechanisms proposed in recent qualitative and conceptual works. However, the modest effect size suggests a more nuanced reality than some optimistic predictions, highlighting that technology alone is not a panacea and must be integrated within robust governance frameworks, a point sometimes underemphasized in the literature. The primary mechanisms identified are enhanced regulatory compliance, reduced information asymmetry, and optimized resource allocation. Governance quality, particularly external monitoring (e.g.,

institutional investors, Big4 auditors) and robust internal controls, acts as a critical amplifier of AI's effectiveness. The analysis also reveals significant heterogeneity, with stronger effects observed in state-owned enterprises, high-emission sectors, and large corporations.

The study contributes to the literature in several ways. It offers, to our knowledge, the first quantitative synthesis of the AI-greenwashing relationship and moves the discussion beyond narrative reviews to a consolidated effect-size estimate. It also bridges dynamic capabilities, agency theory and institutional theory to account for both the direct effects of AI and the moderating role of governance. By focusing on China - a country at the frontier of both AI adoption and ESG data infrastructure - the analysis offers insights from a setting whose patterns may anticipate developments in other economies.

Several important limitations of this research and the underlying studies must be acknowledged, which also define a clear agenda for future research. *First*, the geographic scope is limited to China, limiting the generalizability of findings to other institutional contexts with different regulatory regimes and market pressures. Future research should test these relationships in cross-country comparative studies. *Second*, the measurement of AI adoption primarily through textual analysis and robot counts may not fully capture the depth or effectiveness of implementation. Future studies should employ more granular metrics, such as data on specific AI software deployments, patent portfolios, or specialized workforce. *Third*, the temporal dynamics are not fully explored; longitudinal studies tracking the long-term evolution of the AI-greenwashing relationship are needed. *Finally*, the findings have poor scalability for small and medium-sized enterprises (SMEs), which face resource constraints. Future research should investigate cost-effective, scalable AI solutions and policy supports tailored for SMEs.

Overall, building authentic ESG reporting in the digital age is less about replacing human judgement with algorithms and more about pairing the two: technology should support better governance, and governance should ensure that technology is used responsibly. AI and digital technologies do not on their own resolve greenwashing, but, deployed within strong accountability frameworks, they can meaningfully improve the integrity of corporate sustainability disclosures. The task for researchers, practitioners and policymakers is to create the conditions under which this complementarity actually holds across different types of firms and economies.

On the practical side, the findings position AI and digitalisation as governance-enhancing tools in the ESG domain rather than as ends in themselves. For corporate managers, this means integrating AI into ESG management systems deliberately, with attention to algorithmic transparency and auditability. For regulators, it points to the value of developing AI-augmented tools for greenwashing detection and of designing differentiated support policies for different types of firms. For investors, it suggests that the quality of AI governance inside a firm is itself a relevant signal when judging ESG authenticity. The broader policy implication is that AI is best treated not as a universal solution but as an amplifier of the governance and regulatory mechanisms already in place for promoting sustainable business practice.

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