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AI Integration in ESG Strategies: An Organisational and Institutional Perspective

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Abstract

This study investigates the integration of Artificial Intelligence (AI) into Environmental, Social, and Governance (ESG) strategies, with a focus on institutional and organisational aspects within the context of Greek organisations. Using a quantitative design interpreted through institutional and organisational theory, the study explores how organisations use AI tools to advance sustainability, governance, and ethical goals. Despite the small sample size (N = 82), the study's methodology uses penalised ordinal regression with cross-validation to enforce solid and trustworthy inference. The results indicate that AI maturity is the strongest and most consistent predictor of AI use in ESG reporting, while company size shows a meaningful association only with ESG strategy and sectoral effects remain weak. Drawing on Lipsky's street-level bureaucracy framework and Weber's bureaucracy theory, the study proposes at a theoretical level that interactions between frontline discretion and bureaucratic structures influence the ethical outcomes of AI projects. From an institutional perspective, AI adoption may function as a reputational strategy that enhances symbolic capital and organisational legitimacy. Businesses and organisations with established AI ethics policies acknowledge AI's limited but occasionally significant contribution to social equality, while those without such policies often express uncertainty. Descriptive patterns indicate higher AI activity in certain sectors, although inferential tests show that sector effects are not statistically robust. The study concludes that responsible AI adoption requires ethical training and participatory governance models. Finally, it encourages more cross-country and cross-sector research using advanced analytics and composite indices to better understand institutional dynamics and the sociotechnical complexities of AI-enabled ESG governance. These discoveries improve our theoretical and practical knowledge of the moral application of AI in corporate sustainability.

JEL Classification: M14, O33, L38.
Keywords: Artificial Intelligence (AI), Environmental-Social- Governance (ESG), Quantitative Methods, Institutional Theory, Organisational Sociology

1. Introduction

The rapid incorporation of Artificial Intelligence (AI) into Environmental, Social, and Governance (ESG) strategies is transforming business practices globally. Organisations across sectors are increasingly relying on AI-powered solutions to monitor ESG performance, support sustainability initiatives, and manage regulatory compliance. Significant concerns are raised by this trend regarding the potential adaptability of organisational structures, decision-making procedures, and ethical processes to the demands of AI-enhanced ESG management and governance (Lee et al., 2025; Li et al., 2025). The spread of AI in ESG strategies provides a rich framework for examining the relationship between technological innovation and institutional structures from the perspective of organisational sociology. In order to explain phenomena like the adoption and integration of AI tools within corporate ESG processes, Max Weber's theory of bureaucracy looks at how formal rules and logical processes shape organisational behaviour (Weber, 2019). Lipsky's theory of street-level bureaucracy holds that human actors "in the frontline" are supposed to interpret, implement, and modify AI-driven ESG policies in response to pragmatic or moral considerations.

The Greek institutional and organisational context is a very relevant setting for this study. Greek organisations (such as companies) are increasingly pressured to adapt to new regulations by the European Union. Yet the adoption of AI tools remains uneven, often being contingent on organisational culture, resource availability, and intra-business perceptions of technological legitimacy (Minkkinen & Mantymaki, 2023). The current study examines the ethical, institutional, and organisational aspects theoretically, while empirically analysing patterns of AI maturity and ESG adoption. In particular, it theoretically considers how frontline discretion, organisational structures, and institutional logics may interact to influence ESG-related behaviour. Since the survey did not include direct indicators of discretion, interpretive work, or symbolic-capital processes, these relationships are hypothesised rather than empirically measured (Thornton & Ocasio, 2008; Floridi & Cowls, 2022). It also explores how the use of new technologies may enhance organisational legitimacy and symbolic capital on a theoretical level (Bourdieu, 1986).

The study intends to make multiple contributions to current research by combining the previously mentioned viewpoints. In order to shed light on how ethical and technological issues might be balanced in practice, it applies institutional and organisational theory to the developing field of AI-enabled ESG strategies. In contrast to earlier studies that typically concentrate on technological effectiveness or ESG performance indicators, this work highlights the organisational, ethical, and human aspects of implementing AI with the goal of offering a comprehensive understanding of the sociotechnical environment in which business strategies function (Zuboff, 2023; Brynjolfsson & McAfee, 2014). In this study, "organisations" refers to private firms and non-governmental entities embedded in institutional environments. This study addresses the following overarching research question:

What is the impact of organisational AI maturity on the adoption and development of ESG strategies in Greek institutional firms?

To explore this, the analysis focuses on three specific sub-questions:

1. Does increased AI maturity indicate more AI integration in ESG governance and reporting?

2. Do industry and business size have an impact on how AI maturity and ESG adoption are related?

3. How is the relationship between AI maturity and ESG outcomes shaped by institutional and ethical frameworks (bureaucratic structures, street-level discretion, and symbolic legitimacy)?

From these, the study posits the following hypotheses:

H1: Organisations with greater AI maturity are more likely to incorporate AI into governance and ESG reporting procedures.

H2: Oganisation size and sector may condition patterns of ESG adoption, but their effects are expected to be weaker and more context-dependent than those of AI maturity.

H3: Organisations with established AI ethics policies are expected—at a descriptive level—to report clearer perceptions of AI's fairness and trustworthiness.

H4: Inadequate participatory governance and bureaucratic rigidity hinder the successful application of AI-driven ESG strategies.

In this way, the study provides guidance for managers, lawmakers, and scholars researching organisations who wish to understand how AI adoption in ESG governance functions, especially in circumstances where institutional pressures, technological bets, and ethical considerations interact and overlap.

2. Theoretical Framework

2.1 Organisational Theory & Institutional Analysis

Max Weber's theory of bureaucracy is essentially an overview of how formal organisational structures may in turn influence the integration of new strategies. According to Weber (2019), bureaucracy is characterized by hierarchical authority, standard rules, and a clear division of labor, which collectively aim to increase efficiency, predictability, and accountability in organizations. These structural characteristics influence the implementation, monitoring, and maintenance of AI tools in the context of ESG adoption, guaranteeing that sustainability reporting, compliance systems, and ethical supervision adhere to established protocols. Although AI systems provide automation and analytical capabilities, they must function within these bureaucratic structures in order to obtain regulatory compliance and organisational legitimacy. However, Weberian insights highlight possible conflicts between the flexibility needed for successful AI integration and inflexible bureaucratic structures. Adoption of AI in ESG strategies frequently necessitates adaptive learning, cross-functional collaboration, and quick reactions to social or environmental changes, whereas bureaucracies place a strong emphasis on procedural correctness. Organisations that only use hierarchical decision-making may find it difficult to fully utilise AI-driven insights, especially in context-dependent and dynamic ESG domains (Orlikowski & Barley, 2001; Brynjolfsson & McAfee, 2014). By comprehending these conflicts, researchers can look into how companies strike a balance between the need for innovation in ESG governance and procedural rigour. Additionally, Weber's framework provides analytical tools for investigating authority and legitimacy in ESG decision-making. Organisations that use AI in ESG procedures frequently aim to show investors, regulators, and civil society that they are transparent, compliant, and practice rational governance. By defining roles and duties, bureaucratic structures help guarantee that AI-generated ESG outputs are auditable and defendable, which enhances organisational credibility (Scott, 2008). By connecting organisational theory with current discussions on ESG accountability, and responsible AI trust and usage, integrating AI into these structures not only improves operational efficiency but also strengthens their perceived (symbolic) legitimacy in competitive business fields (Floridi & Cowls, 2022; Lee et al., 2025).

2.1.1 Street-Level Bureaucracy and AI in ESG Implementation

According to Michael Lipsky's theory of street-level bureaucracy, frontline actors—managers, compliance officers, and employees—play a crucial role in analysing, modifying, and carrying out organisational policies (Lipsky, 1980). These actors act as mediators between top-down directives and operational realities in the context of AI-enabled ESG strategies. The effectiveness of these systems relies on the judgement and discretion of those in charge of day-to-day operations, even though corporate leadership may use AI tools to improve sustainability reporting, lower emissions, or track social compliance. As a result, street-level bureaucrats play a crucial role in determining the application, contextualisation, and occasionally modification of AI tools to satisfy local and organisational requirements. Street-level actors face a dual challenge when integrating AI into ESG practices: striking a balance between adaptive problem-solving and procedural adherence. Frontline workers frequently deal with vague or contradictory ESG goals, especially when AI system outputs conflict with ethical standards, resource constraints, or social norms. According to studies, discretion at this level can have a big impact on organisational outcomes like the credibility of environmental initiatives, the dependability of ESG reporting, and the perception of corporate responsibility (Christensen & Laegreid, 2011; Maynard-Moody & Musheno, 2003). AI can improve decision-making by offering risk assessments or predictive insights, but it also adds complexity that calls for contextual knowledge, ethical reasoning, and interpretive skills. Furthermore, the relationship between institutional cultures and technological implementation is clarified by street-level bureaucracy theory. Frontline actors manage conflicts between conflicting priorities, such as regulatory compliance, ethical responsibility, and financial efficiency, in addition to operationalising AI systems. The theory suggests that their behaviour has the potential to influence the legitimacy and social acceptance of AI-driven ESG strategies by reproducing or challenging organisational norms (Lipsky, 1980; Hupe & Hill, 2007). In order to guarantee that AI adoption in ESG domains promotes sustainable and socially responsible outcomes, it is crucial to acknowledge the agency of street-level bureaucrats and to implement ethical guidance, training, and participatory governance.

2.1.2 Institutional Logics and AI in ESG Strategies

The institutional logics framework developed by Thornton and Ocasio (2008) offers a prism through which to view how organisations manage several, frequently incompatible sets of norms, values, and priorities. Businesses function at the nexus of technological, financial, and social logics in the context of AI-driven ESG strategies. The efficiency, predictive ability, and automation potential of AI tools are highlighted by technological logic. Profitability, competitiveness, and shareholder value are given top priority in business and market logics. In the meantime, social and ethical reasoning emphasise corporate responsibility, social justice, and environmental sustainability. The theory of institutional logics aids in the explanation of how organisational decision-makers balance these conflicting demands while incorporating AI into ESG practices.

When institutional logics are applied to the adoption of AI-ESG, it becomes clear how organisational actors understand, defend, and legitimise their technological decisions. Organisations might, for example, use AI-based sustainability checklists to indicate adherence to environmental laws (social/ethical logic), while also increasing operational effectiveness (technological logic) and boosting their standing in the marketplace (business logic). Each logic's importance may differ depending on the sector, national institutional environment, or organisational context. Organisations in Greece, for instance, must contend with a regulatory environment influenced by both local institutional norms that prioritise stakeholder engagement and corporate legitimacy and EU ESG directives (Iatridis & Kesidou, 2018). Determining why some AI-ESG initiatives are successful while others encounter opposition or only partial adoption requires an understanding of these dynamics.

Additionally, institutional logics theory clarifies the role of organisational actors as interpreters and translators of AI technologies. To affect how AI is integrated into business procedures and decision-making, data scientists, managers, and ESG officers resolve conflicts between opposing logics. Their interpretations affect not only the technical performance of AI systems but also how internal and external stakeholders view the symbolic significance of ESG initiatives. Knowing these connections makes it easier to understand how social responsibility, organisational culture, and technological innovation interact in contemporary businesses (Greenwood et al., 2010; Thornton et al., 2012).

2.1.3 Symbolic Capital, Fields, and AI in ESG Strategies

Bourdieu's concepts of symbolic capital and fields offer a helpful lens for analysing the role of AI in ESG strategies, particularly with regard to how companies establish legitimacy and prestige in institutional settings (Bourdieu, 1993). Within this framework, organisations operate in a number of domains, such as economic, social, and technological ones, each with their own set of rules, capital structures, and hierarchies. Symbolic capital, including recognition, prestige, and reputation, becomes an essential resource when organisations employ AI tools to enhance ESG performance. By effectively integrating AI into ESG initiatives to communicate sophistication, moral responsibility, and technological leadership, organisations can acquire symbolic capital that distinguishes them from competitors.

Environmental impact predictive analytics, AI-enabled ESG reporting, and data - driven social compliance systems can serve both pragmatic and symbolic objectives. These practices demonstrate to investors, regulators, customers, and civil society that the business is innovative, responsible, and compliant with contemporary social values. In Greece, where local social norms and EU regulations both have a significant impact on business legitimacy, symbolic capital can have a significant impact on corporate behaviour (Efthalitsidou et al., 2025). Organizations may portray AI adoption as a sign of moral and technological sophistication, thereby potentially strengthening internal commitment to ESG goals and enhancing their reputation in the broader institutional field. Furthermore, symbolic capital acts as a mediator in the relationship between technological systems and organisational actors. According to institutional theory, managers and ESG officers may strategically frame AI capabilities to align ESG innovations with dominant field logics in order to obtain legitimacy Pache & Santos (2013). This point of view emphasises that the use of AI is not only technical but also deeply social and strategic, as companies aim to be recognised for their responsible innovation. Bourdieu's framework thus improves institutional logics and street-level analyses and illuminates how companies manage complex interdependencies between legitimacy, performance, and ethical responsibility by emphasising the relational and reputational aspects of AI in ESG strategies (Pache & Santos, 2013; Boxenbaum & Jonsson, 2017).

3. Conceptual Framework and Model

This study suggests an integrated conceptual framework that connects institutional and organisational determinants of AI-enabled ESG governance, building on earlier theories. The framework organises the empirical analysis by converting the descriptive theoretical discussion into a set of verifiable relationships.

Fundamentally, the model assumes that the main predictor of **AI integration into ESG strategies** is **AI maturity**, or the extent to which an organisation has developed and integrated AI capabilities. However, both institutional and structural factors have an impact on this relationship.

- **Weberian bureaucracy (Weber, 2019)** explains how formalized rules and hierarchical authority can enhance accountability and standardization but may restrict innovation in AI–ESG processes.
- **Street-level bureaucracy** (Lipsky, 1980) emphasizes the discretion of frontline actors whose ethical and contextual judgments shape the practical implementation of AI for ESG.
- **Institutional logics** (Thornton & Ocasio, 2008) capture how firms reconcile competing technological, economic, and social rationalities when adopting AI tools.
- **Symbolic capital** (Bourdieu, 1986, 1993) illustrates how institutions use the adoption of AI to demonstrate their ethical sophistication and legitimacy.

In this configuration, **AI maturity** is expected to positively affect **AI integration into ESG reporting and governance**, which in turn enhances **organisational legitimacy**. Bureaucratic rigidity, limited participatory governance, or weak ethical structures may attenuate this effect, while the presence of established ethics policies and a strong participatory culture are expected to strengthen it.

With the help of the quantitative models and survey indicators discussed in the following section, this framework operationalises the theoretical discussion into quantifiable constructs that can be empirically tested.

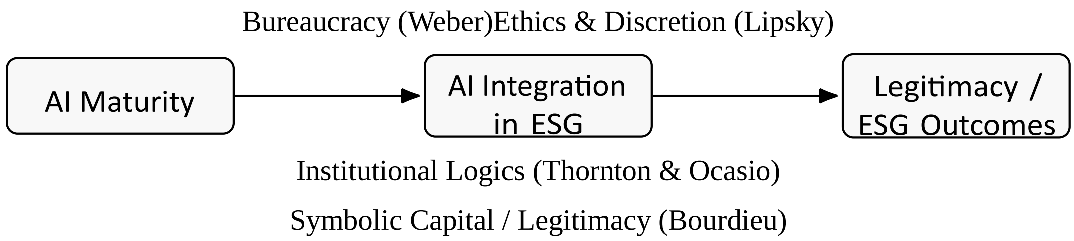


Figure 1: Conceptual model of AI integration into ESG governance. The arrows representing institutional moderators (bureaucracy, ethics, logics) reflect theorised—not quantitatively estimated—relationships.

4. Methodology

This study uses a quantitative research design to investigate how AI is incorporated into ESG strategies in organisations. The primary pillars of the methodology are the research design, sampling strategy, data collection instruments, data processing, and statistical analysis techniques. The approach is based on previous NGO-led research on AI and sustainability to guarantee that the methodology captures both organisational practices and perceived impacts of AI adoption within ESG frameworks.

4.1 Research Design & Sampling Strategy

The study uses a cross-sectional survey design, which makes it possible to gather information from several organisations at one time. Examining the current level of AI adoption in ESG strategies and comprehending how organisations incorporate AI tools into their sustainability, governance, and social responsibility frameworks are two areas in which this design excels. Organisational characteristics (e.g., sector, size, and geographic location), adoption levels of AI, the particular elements of ESG strategies put into practice, and the perceived effects of AI integration on organisational performance and sustainability outcomes are just a few of the dimensions that are the focus of the survey design. This multifaceted approach aimed to capture technical adoption trends and strategic implications The study also integrates best practices from research led by NGOs, such as the use of validated indicators to gauge AI adoption maturity and ESG performance. These metrics capture the modes in AI that are incorporated into sustainability-related decision-making processes while enabling comparability across sectors and organisations. Professionals who work directly in corporate strategy, innovation, sustainability, ESG, and technology roles in a range of organisations make up the target groups. Purposive sampling is used to guarantee the collection of pertinent, high-quality data from Greek Businesses and NGOs. This makes it possible to choose people with real-world experience and active participation in AI adoption for ESG reasons. In order to increase representativeness, the sample is categorised by geographic location, organisation size (small, medium, and large), and sector (energy, finance, manufacturing, and services), with an emphasis on companies that operate in Greece. By using this stratification, the survey captures variations in ESG practices and AI adoption patterns among organisational contexts. The sampling approach is also influenced by the field's NGO research, which represents the inclusion of companies with different degrees of AI adoption and ESG maturity. The study can determine trends, obstacles, and motivators related to AI integration in ESG strategies by capturing this range. While taking into account pragmatic limitations like organisational willingness to participate and data confidentiality concerns, an attempt is made to obtain a large enough sample size to enable reliable statistical analysis. A structured questionnaire is the main tool used to collect data; it is intended to collect quantitative data on important variables. Organisational demographics, AI adoption and usage trends, ESG strategy implementation, perceived results, and difficulties incorporating AI into sustainability initiatives are some of the sections that make up the questionnaire.

Likert scales, closed-ended questions with ranking items to support quantitative analysis, and multiple-choice questions make up the majority of the questionnaire. In order to gather qualitative information about particular organisational practices, difficulties, and success factors, a few open-ended questions are included. The questionnaire was created through a rigorous process that began with a comprehensive review of the literature on AI, ESG, and organisational adoption frameworks in order to identify validated indicators and significant constructs.

A pre-test of the questionnaire was conducted with a small group of professionals from different industries to ensure its validity, reliability, and clarity. The pre-test feedback was utilised to improve the question phrasing, eliminate any ambiguities, and modify the format of the responses. The instrument also incorporates recommendations from NGO research methodologies to make sure that questions on AI adoption capture both technical maturity (such as the kind of AI tools used, as well as integration into decision-making processes) and strategic impact (such as improvements in ESG performance, operational efficiency).

5. Instrument Validity and Reliability

Single-item categorical or ordinal indicators (such as AI Maturity, ESG Strategy, Company Size, and Sector) make up the majority of the questionnaire. Rather than capturing latent psychological constructs, these items were intended to capture distinct organisational characteristics and adoption behaviours. Because they require multi-item scales that measure a common latent dimension, traditional scale-reliability statistics like Cronbach's α and the Kaiser–Meyer–Olkin (KMO) sampling adequacy test are inapplicable.

Questionnaire items were derived from validated indicators used in NGO-led ESG assessments and previous academic studies on AI adoption in order to guarantee content validity. Professionals in ESG and AI roles pre-tested the instrument, and changes were made to enhance face validity and clarity. Bivariate association tests and penalised ordinal regression, which evaluate the coherence and predictive behaviour of the coded variables within the empirical models, are used to analytically address construct validity.

5.1 Data Processing

Firstly, quality checks were performed on the collected data to identify and correct any missing or inconsistent responses. Using statistical diagnostics, outliers and possible mistakes were cross-referenced with the original survey entries. Records with incomplete values on key variables were removed to ensure valid comparisons. A total of 100 surveys were collected, of which 82 were retained after data cleaning. Ordinal variables (*AI Maturity*, *ESG Strategy*, and *AI use for ESG Reporting*) were coded as ordered factors, while categorical variables such as sector and company size were treated as nominal factors. To prevent sparse categories from biasing estimates, rarely represented sectoral categories were combined, and company sizes were grouped into three classes (small, medium, large). Table 1 summarises the variables used in the inferential analysis, their measurement type, and coding.

Table 1: Variables Used in Statistical Analysis

Variable	Description	Type	Scale / Coding
Company Size	Size of the organisation (number of employees)	Ordinal	*Small*: 50–250; *Medium*: 251–1000; *Large*: > 1000
Sector	Industry category of the organisation	Nominal	Top 5 sectors retained; all remaining sectors grouped into *Other*
AI Maturity	Level of organisational AI capability	Ordinal	”No strategy”, ”Pilot”, ”Moderate integration”, ”Fully developed”
ESG Strategy	Existence and development of ESG strategy	Ordinal	”No”, ”Plan in progress”, ”Yes”
AI_ESG Report	Degree of AI use in ESG reporting	Ordinal	”No”, ”Under consideration”, ”Yes (analysis only)”, ”Yes (multiple stages)”
AI_Usage Areas	Functional areas where AI is applied	Nominal	Examples: ”Risk detection”, ”CO_2 monitoring”, ”No use”, etc.

Note. Only variables included in Fisher's tests and penalised ordinal regression models are shown. Ordinal variables were treated as ordered factors during analysis.

After data coding, R was used for all analyses. Likert-scale responses were treated as ordinal data, and sample characteristics and ESG–AI integration patterns across sectors and organisational sizes were summarised using descriptive statistics (mean, median, standard deviation, and frequency distributions). The ggplot2 package was used to create the visualizations.

In five thematic areas—(1) Company Size and ESG Strategy, (2) Sectoral Variation in AI Adoption, (3) AI Maturity and Organisational Trust, (4) AI Usage in ESG Reporting, and (5) Alignment of AI Practices with ESG Goals—the analysis examined how organisational characteristics relate to AI integration and ESG practices. These thematic areas were selected because they represent the core organisational factors most commonly highlighted in ESG and AI adoption research—size, sector, technological readiness, reporting practices, and alignment between AI capabilities and sustainability goals.

Bivariate associations between categorical variables were assessed using **Fisher's exact tests** (10,000 Monte Carlo simulations) and corresponding **Cramer's V** coefficients to evaluate effect size and association strength. These tests quantified relationships such as *Company Size × ESG Strategy* and *AI Maturity × AI use for ESG Reporting*, providing a robust measure of association in small-sample contingency tables.

The study used **penalized ordinal logistic regression** (LASSO, cumulative logit link) implemented via the ordinalNet package to find joint predictors of ESG and AI outcomes while controlling for multicollinearity and overfitting. By automatically selecting variables and reducing non-informative coefficients to zero, this technique enhances the stability and interpretability of the model. Three models were estimated: (1) ESG strategy as a function of sector and company size; (2) AI maturity as a function of sector, company size, and ESG strategy; and (3) AI use for ESG reporting as a function of sector, company size, and AI maturity. The lowest Akaike Information Criterion (AIC) was used to select the model, and odds ratios were calculated for each predictor that was kept in order to show the direction and strength of the effect.

Each model underwent **five-fold cross-validation** to assess model robustness, reporting mean log-likelihood, deviance percentage, misclassification rate, and Brier score. Stronger generalisation performance is indicated by lower misclassification and Brier values. Despite the small sample size, the cross-validation verified that penalisation decreased variance and preserved predictive stability.

The combination of Fisher's tests, penalised ordinal regression, and descriptive visualisation across the five thematic domains produced a thorough, statistically conservative evaluation of the behavioural and structural factors influencing AI adoption in ESG initiatives. The analysis of the organisational, strategic, and technological aspects of AI enabled sustainability practices was made transparent, robust, and repeatable with this method.

The variable "Company Size" refers to the organisational size as determined by the number of employees, even though the sample comprises both private companies and non-governmental organisations (NGOs). The terminology is in line with established corporate governance and ESG literature, where "company size" is typically employed as a structural predictor (Li et al., 2025; Lee et al., 2025). Therefore, the term should be understood to refer to all of the organisations in the sample, regardless of their legal structure, throughout the analysis.

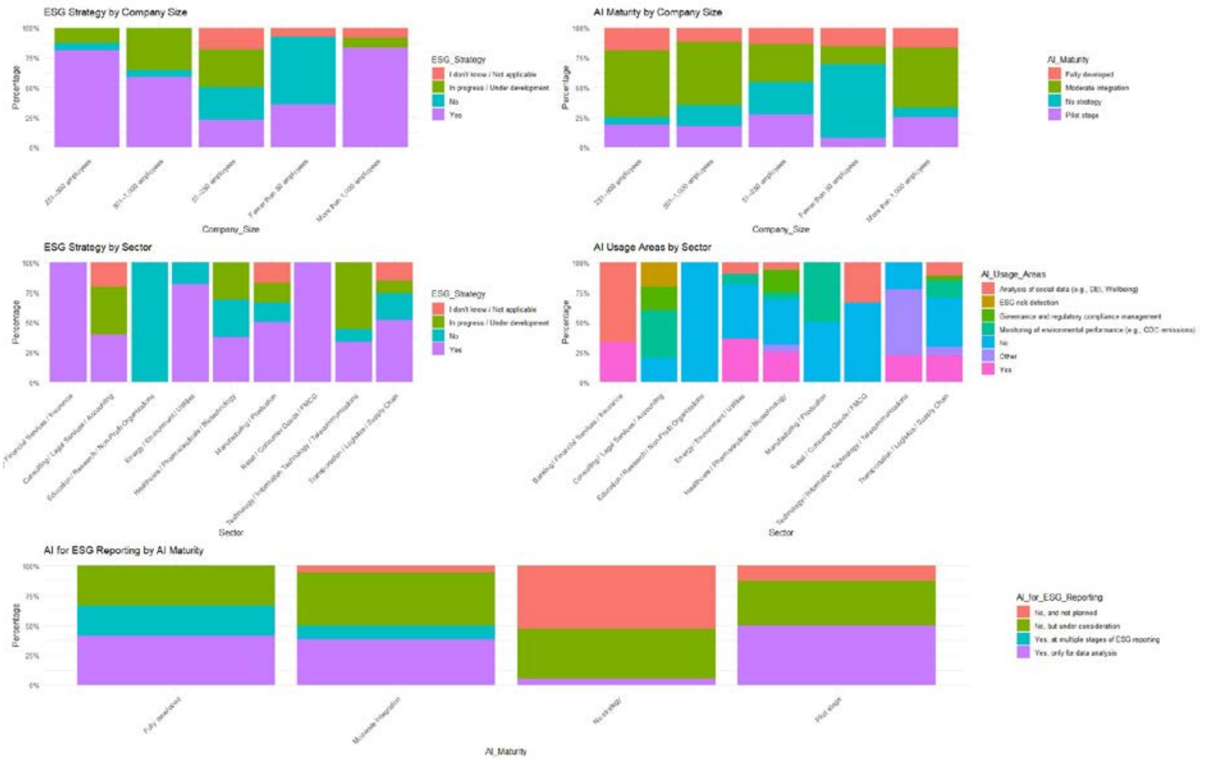
5.2 Ethical Considerations

Ethical compliance is maintained throughout the entire research process. After being fully informed about the objectives, procedures, and rights of the study, including the option to stop participating at any time, all participants provided their informed consent. Anonymity is strictly upheld, data is safely stored, and it is only used for academic research. The study conforms to the norms and moral principles set forth by the relevant institutional review boards and research ethics committees. Particular attention is paid to organisational confidentiality, ensuring that no publications, reports, or analyses reveal any particular answers.

6. Results

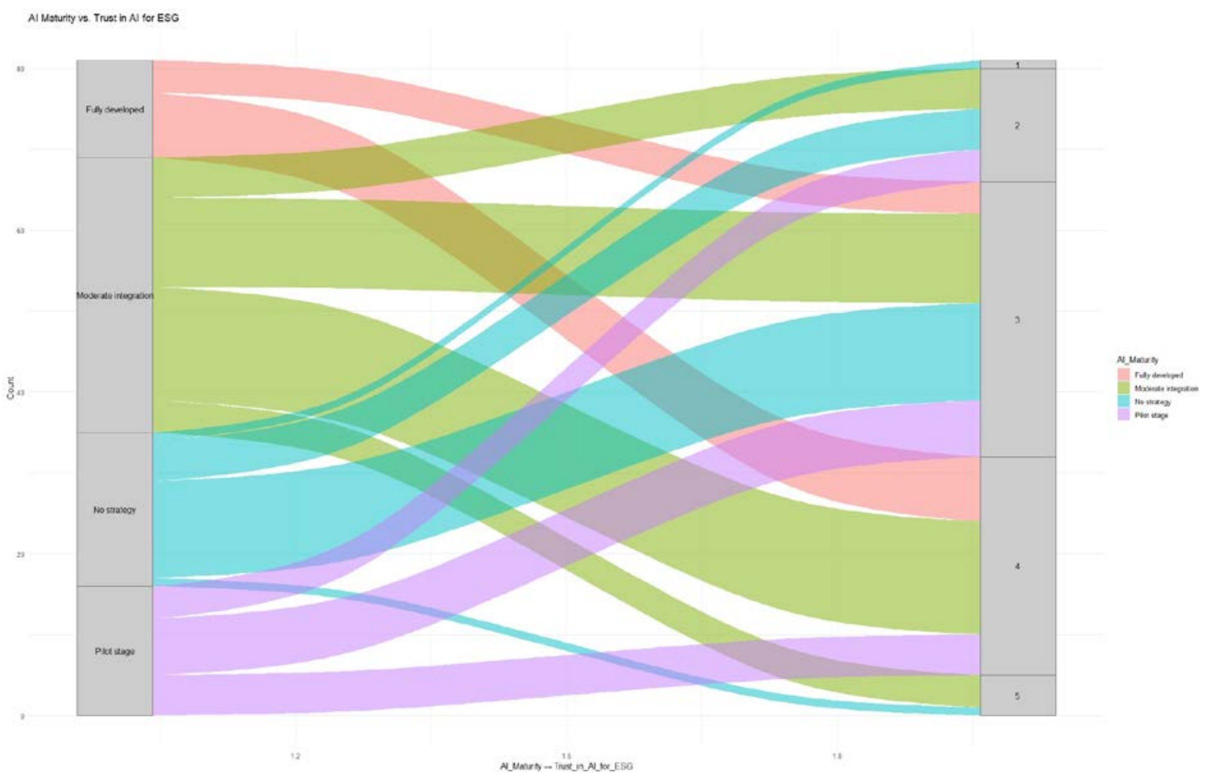
In terms of ESG Strategy × Company Size, the majority of larger organisations do not have an ESG strategy in place; however, organisations with up to 1,000 employees appear to at least have an ESG plan in place. In terms of AI Maturity × Company Size, moderate integration continues to be the most prevalent response, but all company sizes demonstrate a developed maturity in AI usage. The majority of industries claim to have an ESG strategy in place, but telecommunications, education, and biosciences-related industries exhibit the greatest variation in outcomes. A wide range of applications are seen across industries for AI Use Areas per sector. Interestingly, the aforementioned non–ESG-strategic sectors tend to have lower or nonexistent AI usage. However, these sectoral patterns are descriptive only; no statistically significant association between sector and AI use was detected (Table 2). Finally, regarding AI for ESG Reporting by AI Maturity, most maturity levels include at least some planned AI initiative for ESG reporting. These descriptive patterns across company size, sector, and maturity levels are summarised in the proportional bar plots shown in Figure 2.

Figure 2: Proportional bar plots based on the five thematic dimensions of the study



When the relationship between AI Maturity and trust in AI for ESG reporting was analysed, companies with fully developed AI capabilities were equally distributed between medium and medium-high levels of trust in AI for ESG purposes. Organisations with moderate levels of AI integration varied significantly in their responses. Conversely, the majority of organisations that were in the pilot stage or lacked AI maturity reported a medium level of trust in AI for ESG reporting. The distribution of trust levels by AI maturity is visualised in Figure 3. Organisations without a pertinent AI ethics policy typically responded “I don’t know,” when asked if AI helps advance equality. AI contributes to equality to a limited degree, according to organisations that were considering or had drafted an AI ethics policy but had not yet put it into practice.

Figure 3: Alluvial plot on AI Maturity and trust in AI for ESG reporting



Lastly, organisations with a fully operational AI ethics policy stated that, while sometimes significant, AI’s contribution to equality is frequently minimal. These relationships between AI ethics provisions and perceived equality effects are illustrated in Figure 4.

Figure 5 shows how descriptive patterns in AI application areas differ across sectors. The most common uses of AI for ESG reporting among respondents in the Transportation, Logistics, and Supply Chain sectors were innovation benchmarking and risk assessment. Organisations in the utilities and energy/environment sectors also reported using AI at relatively higher levels, especially for innovation benchmarking and ESG reporting. Predictive modelling applications have been the main focus of AI use in technology and telecommunications. Although the heatmap shows clear sectoral differences, inferential tests (Table 2) indicate that sector effects are not statistically robust, so these patterns should only be interpreted as descriptive.

Figure 4: Alluvial plot on AI ethics policy versus whether AI promotes equality

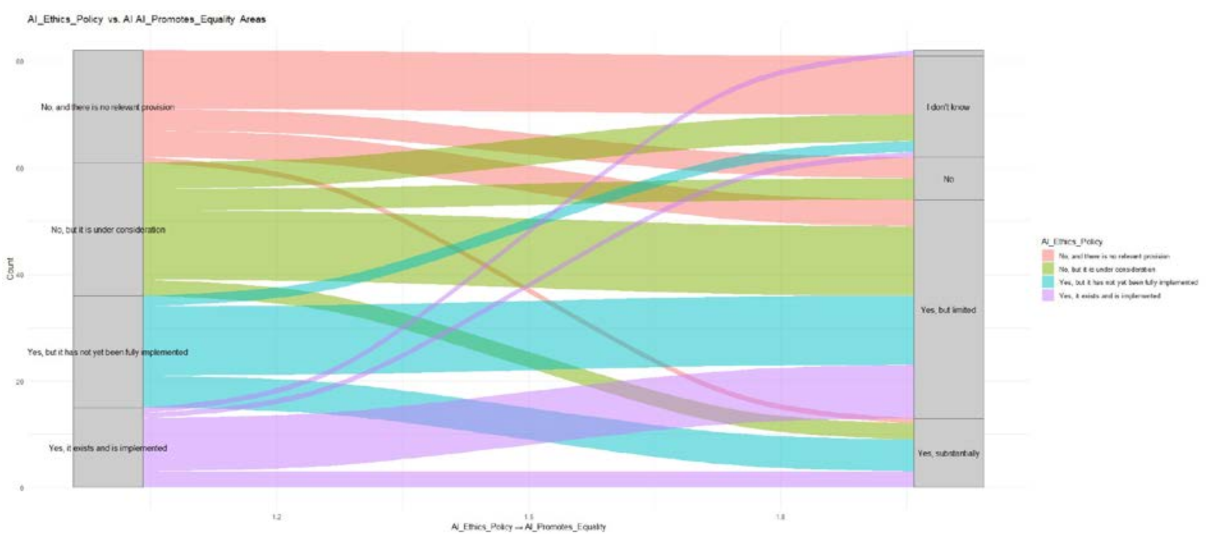
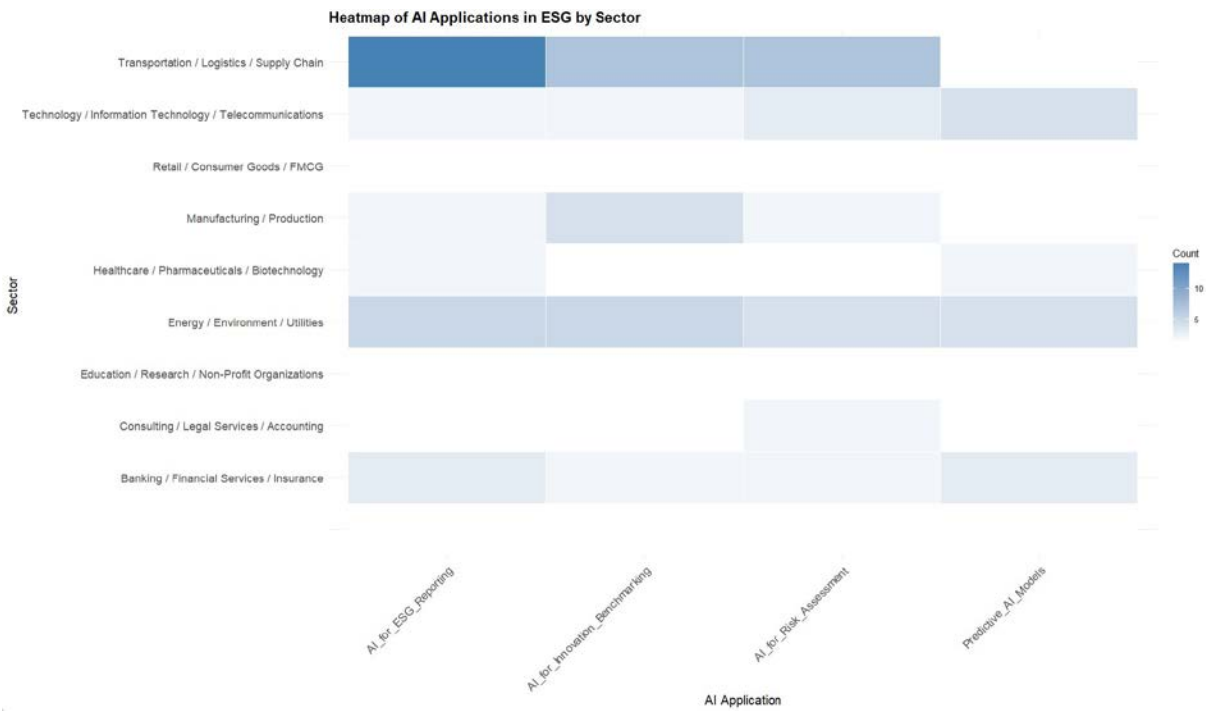


Figure 5: Heatplot on AI usage per company sector



6.1 Inferential Analysis

Fisher's Exact Tests and Cramer's V were used to assess associations between organisational characteristics, AI adoption, and ESG practices. Results revealed a **strong, statistically significant relationship between Company Size and ESG Strategy** (p = 0.0002, V = 0.41), indicating that firm scale is a key determinant of ESG engagement. Likewise, **AI Maturity and AI use for ESG Reporting** were significantly associated ($p < 0.001$, $V = 0.37$), suggesting that organisations with more advanced AI capabilities are markedly more likely to leverage AI in sustainability reporting. Sectoral difference associations were weaker and not statistically significant ($p > 0.05$), suggesting that in this sample, internal technological capability and company size are more powerful differentiators than industry membership.

Table 2: Bivariate Associations Between Organisational Characteristics, AI Adoption, and ESG Practices

Relationship	Fisher's *p*-value	Cramer's V	Interpretation
Company Size × ESG Strategy	0.0002	0.412	Strong association
Sector × ESG Strategy	0.1456	0.299	Moderate, ns
Company Size × AI Maturity	0.0863	0.261	Weak–moderate
AI Maturity × AI for ESG Reporting	< 0.001	0.368	Moderate association
Sector × AI Usage Areas	0.1041	0.356	Moderate, ns

Note. Fisher's exact tests were performed using 10,000 Monte Carlo simulations. Cramer's V values represent effect size: 0.1–0.3 = weak, 0.3–0.5 = moderate, >0.5 = strong. "ns" indicates non-significant association at $\alpha = 0.05$.

To examine these effects jointly and avoid overfitting given the limited sample, **penalised ordinal logistic regression** (LASSO, cumulative logit link) was applied to three models: *ESG Strategy*, *AI Maturity*, and *AI for ESG Reporting*. This approach automatically selects only the predictors that provide stable explanatory power, thereby improving model interpretability and generalisability. In the model predicting *ESG Strategy*, two predictors were retained at the AIC-optimal penalty: **Small Company Size** ($\beta = 1.19$, OR = 3.3) and **Technology/IT/Telecommunications Sector** ($\beta = 0.68$, OR = 2.0). Smaller, technology-focused organisations are roughly two to three times more likely to have a more developed ESG strategy than larger, non-technology-focused organisations, according to all other coefficients that shrunk to zero.

Table 3: Penalised Ordinal Regression Results (LASSO, Cumulative Logit Link)

Predictor	Coefficient (β)	Odds Ratio (OR)	Model
ESG Strategy Model Company Size: Small	1.19	3.30	ESG Strategy
Sector: Technology/IT/Telecom	0.68	1.97	ESG Strategy
AI Maturity Model (No predictors retained)	–	–	AI Maturity
AI for ESG Reporting Model AI Maturity (linear)	0.98	2.66	AI for ESG Reporting
AI Maturity (quadratic)	–2.08	0.13	AI for ESG Reporting
AI Maturity (cubic)	–1.89	0.15	AI for ESG Reporting
Company Size: Large	1.79	5.99	AI for ESG Reporting
Sector: Healthcare/Pharma/Biotech	1.78	5.93	AI for ESG Reporting
Sector: Manufacturing/Production	–0.84	0.43	AI for ESG Reporting
Sector: Technology/IT/Telecom	0.68	1.98	AI for ESG Reporting
Sector: Transportation/Logistics	–0.40	0.67	AI for ESG Reporting
Sector: Other	1.18	3.26	AI for ESG Reporting

Note. Coefficients (β) are from penalised ordinal logistic regressions with LASSO regularisation. Odds Ratios (OR) are computed as e^{β}. Non-retained predictors were shrunk to zero and omitted. Model selection based on minimum Akaike Information Criterion (AIC).

The *AI Maturity* model retained no predictors after penalisation, meaning that company size, sector, and ESG strategy did not add meaningful explanatory value once model complexity was controlled. In contrast, the model predicting *AI use for ESG Reporting* retained several predictors, with **AI Maturity** emerging as the dominant driver (β = 0.98, OR = 2.66). The negative quadratic and cubic contrasts ($\beta \approx -2.1$ and -1.9, OR ≈ 0.13–0.15) suggest a nonlinear relationship: as firms progress in AI maturity, the probability of using AI for ESG initially rises but plateaus at higher maturity levels.

6.2 Model Validation

Five-fold cross-validation demonstrated moderate predictive performance (Table 4). The *ESG Strategy* and *AI for ESG Reporting* models achieved mean misclassification rates of 0.48 and 0.50 and Brier scores of 0.62 and 0.63, respectively, indicating stable generalisation. The *AI Maturity* model performed less well (misclassification = 0.64; Brier = 0.75), consistent with its lack of retained predictors. These results confirm that penalisation effectively mitigated overfitting and maintained predictive stability despite the modest sample size.

Table 4: Cross-Validation Performance (Mean Across Five Folds)

Model	Mean Log-Lik.	Deviance (%)	Misclassification	Brier Score
ESG Strategy	–18.78	–0.05	0.48	0.62
AI Maturity	–22.33	–0.15	0.64	0.75
AI for ESG Reporting	–18.42	+0.00	0.50	0.63

Note. Values represent mean performance across five cross-validation folds. Lower misclassification and Brier scores indicate stronger predictive accuracy. Negative deviance percentages reflect minor sampling variation around zero and are not substantively meaningful.

6.3 Summary of Findings

Overall, the findings indicate that: (1) AI maturity is the primary enabler of AI-driven ESG reporting; (2) sectoral effects are minimal; and (3) smaller and technology-intensive firms lead in ESG strategic development. The penalised models offer a clear, data-driven explanation of the organisational factors influencing AI integration in ESG governance by providing reliable, conservative estimates that strike a balance between interpretability and statistical reliability.

7. Discussion

Organisational paradigms, institutional structures, and ethical governance models are all put to the test when AI is incorporated into ESG strategies. Strong evidence about how organisational traits and technological capabilities influence the spread of AI within ESG practices is provided by the empirical analysis, which combines Fisher’s tests, effect-size estimation, and penalised ordinal regression with cross-validation.

7.1 Key Empirical Insights

Three main relationships emerge. First, **AI maturity is the strongest predictor** of AI integration in ESG reporting. Organisations with higher technological readiness are substantially more likely to employ AI for sustainability reporting, risk assessment, and decision support. Second, **company size and sector have weaker and more inconsistent effects**, suggesting that AI adoption depends less on structural attributes and more on internal capacities and culture. Third, **descriptively, organisations with ethics**

policies report clearer perceptions of equality and trust: firms with established ethics policies report clearer—though still modest—confidence in AI's fairness and transparency.

These findings are supported by significant associations between company size and ESG strategy (p = 0.0002, V = 0.41) and between AI maturity and AI use for ESG reporting (p < 0.001, V = 0.37). The penalised ordinal models further confirm that *Small Company Size* (β = 1.19, OR = 3.3) and the *Technology/IT/Telecom Sector* (β = 0.68, OR = 2.0) predict more developed ESG strategies, while *AI Maturity* (β = 0.98, OR = 2.66) is the dominant driver of AI use for ESG reporting. Cross-validation results (misclassification ≈ 0.48–0.50; Brier ≈ 0.62–0.63) confirm the models' stability.

7.2 Evaluation of Hypotheses

The evidence offers partial but strong support for the study's hypotheses. **H1** is supported: AI maturity consistently predicts AI integration in ESG reporting. **H2** receives partial support: smaller firms are more likely to report developed ESG strategies, but sectoral moderation is weak. These findings suggest that company size exhibits a strong relationship with ESG strategy but does not meaningfully predict AI maturity or AI use for ESG reporting. **H3** is partially supported: ethics policies correlate with clearer perceptions of AI's fairness and trustworthiness. **H4** is supported to the extent that bureaucratic rigidity and absent ethical governance appear to hinder the effective implementation of AI-driven ESG strategies.

7.3 Interpretation through Organisational and Institutional Theory

The results are consistent with Weber's (2019) theory of bureaucracy, which contends that procedural rationality and hierarchical structures give organisations legitimacy and accountability. This is reflected in the relationship between business size and ESG strategy: larger organisations prioritise compliance, whereas smaller, less bureaucratically constrained organisations seem more flexible when incorporating ESG practices. This exemplifies Weber's conflict between innovation and formalisation.

Lipsky's (1980) idea of street-level discretion is consistent with the crucial role of AI maturity. Although AI systems offer analytical capabilities, algorithmic inputs are ultimately interpreted, modified, or resisted by frontline actors. The non-linear pattern in the relationship between AI maturity and ESG reporting indicates that institutional learning, ethical consciousness, and human judgement are still crucial for achieving better ESG results.

The theory of institutional logics (Thornton & Ocasio, 2008) provides an explanation for how organisations manage conflicting technological, market, and social rationalities. Organisations that are successful in integrating AI with ESG objectives seem to reconcile these logics by utilising AI to attain both moral legitimacy and operational efficiency. The small sector effects show that internal alignment of logics, rather than just industry norms, determines adoption.

The use of AI by organisations to maintain reputational legitimacy is further explained by Bourdieu's (1986) concept of symbolic capital. AI-enabled ESG procedures serve as both technical instruments and indicators of technological sophistication and ethical responsibility. The idea that Organisations build symbolic capital by exhibiting responsible. The moderate association between AI maturity and trust can be interpreted, at a theoretical level, as consistent with Bourdieu's concept of symbolic capital

7.4 Ethical and Governance Implications

The study demonstrates how perceptions of equality and trust are significantly influenced by AI ethics regulations. In line with Floridi and Cowls' (2022) assertion that both technical safeguards and cultural embedding are necessary for principled AI governance, firms with formalised ethics provisions express more coherent expectations regarding AI's social impact. These ethics-related patterns are descriptive only: the corresponding variables were not included in Fisher's tests or penalised ordinal regression models, and thus no inferential claims are made. On the other hand, worries about top-down ethical formalism are reflected in the uncertainty among Organisations that do not have such policies (Zuboff, 2023). These results show that operational discretion, staff training, and participatory governance are necessary for significant ethical results.

7.5 Integrating Empirical and Theoretical Contributions

The study makes two contributions to organisational sociology by fusing institutional theory with penalised modelling. Empirically, the analysis offers statistically conservative proof of how institutional conditions and organisational traits influence ESG integration. Theoretically, it demonstrates how bureaucratic order, moral judgement, and symbolic capital interact to create legitimacy in AI-ESG governance. This presents AI-enabled ESG as an area where ethical and technological performance are mediated by organisational structure.

7.6 Policy and Managerial Implications

The empirical results offer a number of policy-relevant insights into the integration of AI with ESG governance. Policies should place a higher priority on enhancing organisations' technological and analytical capabilities since AI maturity turned out to be the best and most reliable predictor of AI-enabled ESG reporting. This means that managers and regulators must concentrate on organised capacity-building projects, such as internal training programs, data infrastructure investments, and organisational mechanisms that facilitate AI tool experimentation. The statistical evidence demonstrating that organisations with higher levels of AI maturity were more than twice as likely to use AI for ESG reporting (OR = 2.66) is directly consistent with these interventions.

Agility and less bureaucratic inertia may encourage ESG experimentation, as evidenced by the finding that smaller organisations are significantly more likely to have established ESG strategies (OR = 3.30). This suggests that managers in larger organisations must empower cross-functional teams, lessen internal rigidity, and establish "innovation pockets" within hierarchical structures. From a policy perspective, industry associations and regulators should encourage the adoption of lighter, more adaptable governance procedures by organisations in order to support bottom-up AI-ESG initiatives.

Industry-specific factors are not the primary drivers of AI-ESG adoption, as evidenced by the weak and inconsistent sectoral effects. This finding suggests that rather than sector-specific or narrowly targeted regulations, policymakers should favour horizontal instruments that support AI-enabled ESG governance across all sectors. Incentives should focus on enhancing AI literacy, data governance standards, and ethical awareness throughout the entire organisational ecosystem since AI capabilities—rather than sector membership—are what distinguish adopters from non-adopters.

Lastly, the empirical finding that AI ethics policies are associated with more accurate judgements of justice and trust emphasises the significance of formal ethical governance frameworks. The legitimacy of AI–ESG integration is influenced by ethical embedding, as evidenced by the more coherent expectations about AI's social impact displayed by organisations with established ethics provisions. Therefore, managers ought to make investments in the creation of workable ethical standards, internal auditing systems, and employee education regarding responsible AI use. Regulatory incentives, standard setting, and guidance documents in line with EU AI governance frameworks are ways that policymakers can assist this.

7.7 Policy Implications for the Greek Context

The results are particularly pertinent to Greece, where adoption of ESG and digital transformation is still uneven among different types of organisations. A national strategy aimed at boosting AI readiness is crucial, since AI maturity was the only reliable predictor of AI-enabled ESG reporting. Greek organisations, especially SMEs, frequently fall short of EU averages in terms of data infrastructure and digital skills. This gap would be directly addressed by targeted funding through national recovery programs, training subsidies, and collaborations with research institutions. This would be consistent with the study's findings that ESG innovation is driven by AI capability rather than sector or size alone.

Smaller Greek organisations may be more flexible in implementing ESG practices, whereas larger organisations encounter Weberian bureaucratic rigidities, according to the strong correlation between company size and ESG strategy. Greek regulators should support larger organisations in implementing internal governance reforms that empower cross - departmental teams and eliminate procedural bottlenecks, as this has direct policy implications. This is in line with Greece's Digital Transformation Bible 2020–2025, which places a strong emphasis on streamlining public–private governance structures and organisational agility.

The data's weak sectoral differences suggest that Greek policy should promote horizontal frameworks in line with EU directives like CSRD and the EU AI Act rather than overemphasising sector-specific ESG guidelines. Horizontal policies would lessen regulatory fragmentation while giving Greek businesses organisations consistent guidelines for AI-enabled ESG reporting.

Lastly, the study's conclusion that ethics regulations enhance perceived justice and trust points to a definite chance for Greek legislators to advance codified AI ethics frameworks. Since there are currently no widely accepted corporate AI ethics standards in Greece, sector-neutral codes of practice, certification programs, or required ethics audits could be issued by government organisations and trade associations. In addition to encouraging responsible innovation, such measures would help Greek organisations build symbolic capital and strengthen their credibility in both domestic and EU markets.

7.8 Methodological Limitations

Although the study offers a statistically sound analysis of AI integration into ESG strategies, it is important to recognise a number of methodological limitations. First, by using a cross-sectional survey design, organisational practices and perceptions are recorded at a specific moment in time. This makes it more difficult to determine causal relationships or track the development of ESG adoption and AI maturity. The stability of the relationships found here—especially between AI maturity, ethics regulations, and ESG reporting—under shifting institutional pressures and technological advancements could be evaluated through longitudinal research.

Second, the small sample size and categorical structure of the data limit generalisability even though cross-validation and penalised ordinal regression (LASSO) were used to reduce overfitting and improve model stability. By reducing weak coefficients to zero, LASSO produces conservative estimates, which means that subtle or context-specific relationships might go unnoticed. However, by confirming consistent model behaviour across subsamples, five-fold cross-validation reduces these risks.

Third, self-reported data introduces potential biases such as social desirability and strategic answering, just like in most survey-based research. Participants may have overreported or underreported aspects of AI or ESG engagement despite careful question design and guarantees of anonymity, especially on delicate subjects like ethical policy or equality outcomes. Statistical representativeness is further limited by the purposive sampling of experts in AI and ESG roles. Lastly, the study's emphasis on the Greek business environment may limit the findings' external validity in institutional settings with different regulatory, cultural, or technological conditions, even though it is useful for contextual insight.

7.9 Future Outlook

The scope and scale of analysis should be increased in future studies. Studies that are comparative and cross-national may be able to document differences in the regulatory frameworks, cultural expectations, and institutional pressures related to AI-enabled sustainability governance. More sophisticated inferential methods, like multilevel modelling, structural equation modelling, or machine learning classifiers, would be able to more accurately analyse hierarchical and interactive effects with larger and more balanced samples.

In terms of methodology, combining longitudinal data with penalised estimation would improve causal inference and enable researchers to monitor changes in AI maturity, ESG integration, and ethical performance over time. Interpretations of AI–ESG dynamics would be enhanced by theoretically informed quantitative analysis, especially by shedding light on the discretionary actions of managers and compliance officers that this study highlights. The development of cross-sector indices measuring *institutional legitimacy*, *AI maturity*, and *ethical embedding* could provide standardised benchmarks for evaluating organisational progress.

Lastly, more research on the institutional and social dynamics of AI ethics governance should be done in the future. By mapping interactions between organisations, regulators, and stakeholders, network-analytic techniques could show how legitimacy and trust develop within AI-ESG ecosystems. Comparative studies with other EU members would be particularly helpful for the Greek context because they would make it clear whether the patterns seen here are indicative of national institutional peculiarities or more general European regulatory trends.

8. Conclusion

In the context of Greek business, this study investigated how organisational, institutional, and technological factors influence the incorporation of AI into ESG strategies. The results show that while company size and industry have less significant and more erratic effects, AI maturity is the most reliable factor influencing AI-enabled ESG reporting. The study offers a methodologically sound and theoretically sound explanation of how bureaucratic structures, frontline discretion, and symbolic legitimacy influence AI-ESG adoption by fusing institutional theory with penalised ordinal regression and cross-validation. The findings demonstrate that effective ESG innovation requires organisational flexibility, ethical embedding, and cogent governance practices—technological capability alone is insufficient. Strengthening AI readiness and ethical capacity becomes a top priority for organisations and policymakers alike as Greece and other EU economies move towards more stringent ESG and AI regulations. In order to evaluate these patterns' generalisability and enhance comprehension of the sociotechnical dynamics of responsible AI use in sustainability governance, future research should validate them in larger, cross-national samples.

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