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RESEARCH ARTICLE OPEN ACCESS

The Dark Side of AI Readiness? Institutional Logics, Signalling and Carbon Transition Risk

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ABSTRACT

The influence of institutional environments on corporate sustainability is well established, yet how digital readiness restructures institutional logics and signalling mechanisms through which firms manage carbon transition risk (CTR) remains undertheorised. We address this gap by investigating how country level artificial intelligence readiness (AIR) interacts with corporate governance structures and internal climate policies to shape firms' exposure to CTR. Drawing on institutional logics and signalling theory, we conceptualise AIR as a macro-institutional condition that simultaneously enhances firms' technical capacity for transition risk management and reorders the hierarchy of logics through which sustainability is interpreted and legitimised. Using panel data from 5363 sample firms between 2020 and 2023, we find that AIR is associated with lower CTR, reflecting improved information processing, forecasting and technocratic risk management capabilities. However, AIR also has a dark side. As AIR increases, the risk mitigating effects of governance and climate policies weaken or reverse, as these mechanisms are subsumed under market-state logics and repurposed as sustainability signals. This enables symbolic compliance, erodes disciplinary control and shifts legitimacy from carbon reduction to visible digital competence. Our findings contribute to existing sustainability and governance discourse by reconceptualising AIR as an institutional condition, showing that its effects on CTR are contingent on governance, institutional logics and signalling incentives thereby advancing a contingent theory of AI-enabled sustainability governance. By integrating signalling and institutional logics, we offer explanations as to why governance and climate policies lose effectiveness in AI-ready contexts and reframe CTR as an outcome of institutional alignment rather than technological capability.

JEL Classification: G30, G32, G34, Q54, Q58

1 | Introduction

Climate change, driven primarily by greenhouse gas (GHG) emissions, represents one of the most pressing challenges facing contemporary societies and organisations (UNFCCC 2025). The 2016 Paris Agreement marked a decisive shift towards low carbon economic systems, with governments committing to decarbonisation pathways, net zero targets and carbon neutrality by midcentury (Eicke and Goldthau 2021; UNFCCC

2025). Although there is increasing policy support, progress towards low carbon economies remains both uncertain and inconsistent. A primary issue for businesses is carbon transition risk (CTR), which refers to financial and operational uncertainties arising from climate policy changes, shifts in market dynamics and technological advancements (Bolton and Kacperczyk 2023b; Hoang et al. 2025). Instruments such as carbon taxes, emissions trading schemes and mandatory disclosure regimes (e.g., the EU Corporate Sustainability

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Reporting Directive) expose firms to asset revaluation, cost escalation and strategic disruption (Balachandran and Nguyen, 2018). Reflecting this concern, a 2023 BlackRock (Segal 2024) survey reported that nearly half of senior managers rank CTR among their top strategic priorities. As such, there have been calls for measures to mitigate the risks associated with the transition to a low carbon economy.

Artificial intelligence (AI), defined as systems that generate predictions, recommendations or decisions influencing physical or virtual environments (Organisation for Economic Co-operation and Development (OECD) 2024), has been highlighted for its role in facilitating carbon reduction initiatives and supporting transition management strategies (Roux et al. 2025). These include real-time emissions tracking, process optimisation and data-informed decarbonisation strategies (Tseng and Lin 2024). AI also contributes to supply chain transparency and coordination, particularly in addressing Scope 3 emissions using predictive analytics, supplier collaboration and scenario planning (Belhadi et al. 2022). These functionalities indicate that AI can be instrumental for organisations seeking to anticipate, manage and mitigate CTR.

Similarly, current academic and policy perspectives often presume a complementary relationship among AI implementation, governance practices and sustainability achievements. Within this prevailing framework, increased digital capabilities are associated with improved information processing, enhanced oversight of governance and strengthened capacity to address transition risks (Mustafa et al. 2025; Siddik et al. 2025). Some of these assumptions may warrant closer scrutiny, as empirical outcomes are frequently inconsistent or contradictory. For instance, while AI can enhance emissions monitoring and reporting, greater access to information does not automatically result in meaningful decarbonisation (Leal Filho et al. 2022). Moreover, governance arrangements and internal climate policies, commonly regarded as stabilising elements, have at times been linked to increased emissions (Tanthanongsakkun et al. 2023), insufficient disclosures (Alayat et al. 2026) or superficial compliance (Cheng and Wu 2025). These discrepancies highlight a fundamental theoretical gap concerning the boundary conditions under which digital readiness and governance mechanisms cease to strengthen sustainability objectives.

This gap points to a broader limitation in how sustainability research conceptualises AI. Existing studies often treat AI either as a neutral analytical tool or as a capability that enhances efficiency, adaptability and decision quality (Gupta et al. 2022; Rahman et al. 2026). However, such perspectives often overlook how digitalisation reshapes organisational priorities, risk perceptions and responses to sustainability challenges. In highly digitalised environments, firms may respond to CTR primarily through optimisation, abstraction and disclosure-based practices, rather than through substantive changes to carbon-intensive production systems (Yang et al. 2023). Under these conditions, AIR may, paradoxically, obscure rather than resolve deeper transition vulnerabilities. It may, therefore, suggest that the sustainability implications of AI cannot be understood independently of the institutional conditions in which it is embedded (Leal Filho et al. 2022). As such, AIR reflects a broader national

level environment that enables or constrains the integration of AI into organisational decision making, encompassing digital infrastructure, regulatory frameworks, human capital, innovation capacity and governance systems (Yang and Huang, 2022; Shonhe et al. 2024). We argue that how firms leverage AIR is shaped by the institutional logics and signalling incentives embedded within governance frameworks. Institutional logics refer to the various socially constructed systems of values and norms that guide organisational behaviour and shape what constitutes legitimate action (Thornton and Ocasio 2008). In sustainability contexts, environmental and stakeholder logics emphasise substantive decarbonisation and long-term legitimacy (Batista et al. 2023), whereas market logics prioritise efficiency, competitiveness and short-term value preservation (Milosevic et al. 2023).

These logics often coexist in tension and may be particularly pronounced in AI-ready environments, as the signal for which sustainability performance is judged may change. For instance, firms operating in a high AIR environment may face strong incentives to signal technological sophistication, readiness for compliance and data-driven governance. As a result, AI enabled tools, such as carbon dashboards, predictive models and advanced disclosures, may serve as signals of sustainability commitment (Sariyer et al. 2024) even when underlying production systems remain carbon-intensive (Wang et al. 2025). This creates a paradox in which AI may improve efficiency and reduce emissions, while market driven pressures can also reinforce rebound effects and symbolic compliance. Governance, thus, risks becoming a vehicle for legitimising firms through digital sophistication rather than genuine decarbonisation. As such, in AI ready environments, sustainability effects depend on how governance structures and institutional logics shape the use of AI (Chishti et al. 2024). Against this backdrop, we examine how AIR influences CTR and how corporate governance structures and internal climate policies condition this relationship in digitally advanced contexts. Specifically, we address the following research questions:

RQ1. Does AIR provide firms with an institutional environment that enables the management of carbon transition risk?

RQ2. Do governance structures and internal climate policies mediate the relationship between AIR and carbon transition risk when sustainability is evaluated through competing institutional logics and signalling demands?

By integrating institutional logics and signalling theory, our research questions examine whether AIR facilitates CTR and whether the link redefines sustainability governance from a disciplinary mechanism to a signalling device in digitally advanced contexts. In doing so, the study contributes to sustainability, governance and digitalisation literatures by demonstrating that macro-level digital readiness can both enable and constrain firm-level carbon transition outcomes. We contribute to research on AI and sustainable transitions by showing that digital readiness does not uniformly reinforce decarbonisation; it can either strengthen or undermine sustainability governance, depending on the alignment of institutional logics, governance structures and signalling incentives.

The remainder of the paper is structured as follows. Section 2 develops the theoretical framework and hypotheses. Section 4 outlines the methodology and data. Section 5 presents the empirical findings. Section 5 discusses implications, limitations and directions for future research.

2 | Theory and Hypothesis Development

2.1 | Institutional Logics and Signalling Theory

As a core concept in institutional theory, institutional logics refer to socially constructed systems of values, norms, practices, beliefs and rules that shape how organisations interpret their environment and guide behaviour within a given institutional domain (Thornton and Ocasio 2008). Through institutional logics, organisations reproduce social reality, organise time and space and attribute meaning to strategic actions. Institutional logics, therefore, provide decision-makers with interpretive frameworks that align organisational behaviour with industry conventions, societal expectations and regulatory standards, linking firm level action to broader institutional processes (Glaser et al. 2024). A central tenet of institutional logics theory is that firms operate within pluralistic institutional environments in which multiple logics coexist and compete (Thornton et al. 2012). In sustainability contexts, firms are simultaneously subject to regulatory, state, market and environmental or stakeholder logics (Carmagnac et al. 2024; Schumm and Niehm 2024). Each logic prescribes distinct norms, performance criteria and sources of legitimacy, often generating tensions that firms manage through prioritisation, compartmentalisation or decoupling strategies (Bitektine and Song 2023).

In this study, AIR represents a macro-level institutional configuration that embeds digital technologies within governance, regulation and innovation systems (Thornton et al. 2012; Scott 2014). It reflects state logic through national digital infrastructure, public investment, data governance frameworks and policy initiatives that legitimise AI as a tool for economic competitiveness and climate governance (Zuboff 2019; European Commission 2021; Wirtz et al. 2023). Market logic further reinforces AIR by positioning AI as a driver of productivity, optimisation and strategic advantage, encouraging firms to deploy AI to enhance efficiency and profitability (Nambisan et al., 2019; Kraus et al. 2021). In contrast, environmental and sustainability logics emphasise ethical responsibility, long-term stewardship and substantive emissions reduction, framing AI to support decarbonisation and responsible innovation (Buzzao and Rizzi 2021; George and Schillebeeckx 2022).

The interaction of these logics situates AIR within an institutional field characterised by intersecting technological, governance and normative imperatives. Whether AI functions as a transformative enabler of low carbon transition or as a symbolic response to institutional pressures depends on how firms navigate complementarities and tensions among these logics (Thornton et al. 2012; Shalique et al. 2022). Logic plurality, could therefore, directly shape firms' exposure to CTR. In high

AIR environments, where state and market logics may dominate, AI deployment can prioritise optimisation, abstraction and reputational management rather than substantive decarbonisation, thereby masking underlying vulnerabilities and potentially exacerbating transition risk (Bolton and Kacperczyk 2023b; Hoang et al. 2025).

However, while institutional logics theory is well-suited to explaining why competing value systems shape organisational responses, it is less equipped to clarify how firms translate these logics into observable actions under conditions of uncertainty and scrutiny. Institutional logics theory tends to underspecify the mechanisms through which organisations manage external evaluations and legitimacy when substantive outcomes are difficult to observe (Bitektine and Song 2023). This limitation is especially salient in digitally advanced contexts, where sustainability performance is increasingly assessed through proxies such as disclosures, metrics and technological sophistication rather than direct emissions outcomes (Alessi et al. 2024). As a result, institutional logics theory alone cannot fully explain why governance structures and climate policies may persist in form yet lose effectiveness in practice (Vendula et al. 2022).

To address this limitation, we draw on signalling theory, which focuses on how organisations communicate quality, intent and legitimacy to external audiences under conditions of information asymmetry (Spence 1973; Connelley et al. 2011). From a signalling perspective, firms facing uncertainty about the outcomes of the carbon transition may rely on visible, costly and credible signals, such as AI enabled monitoring systems, advanced disclosures and formal governance structures, to convey their sustainability commitment to investors, regulators and stakeholders. In high AIR environments, digital sophistication itself becomes a powerful signal, allowing firms to demonstrate compliance and responsibility even when underlying production practices remain carbon intensive. By combining institutional logics and signalling theory, this study explains not only how competing logics shape sustainability priorities but also how they are enacted through signalling strategies that substitute for substance. In contexts where market and state logics dominate, governance mechanisms and internal climate policies may be repurposed as signals of technological competence and regulatory alignment rather than as constraints that discipline carbon intensive behaviour. This dynamic facilitates symbolic compliance, decoupling and legitimacy acquisition without substantive decarbonisation (Christensen et al. 2021).

In doing so, this study extends institutional logics theory by highlighting the importance of signalling mechanisms in digitally advanced institutional environments. We also reconceptualise CTR as an outcome of institutional and signalling alignment rather than technological capability or market exposure alone. By positioning AIR at the intersection of institutional logics and signalling dynamics, we explain how digital readiness can enable and constrain firms' capacity to achieve legitimate, resilient and substantive low-carbon transformation under competing institutional orders.

2.2 | Artificial Intelligence Readiness and Carbon Transition Risk

CTR arises from the uncertainty and disruption associated with the shift towards low carbon economies (Semieniuk et al. 2021; Bolton and Kacperczyk 2023b). It encompasses risks related to asset devaluation, carbon taxation, regulatory compliance costs, technological obsolescence and reputational exposure (Palea and Drogo 2020). Crucially, CTR is dynamic and systemic, shaped not only by firms' direct (Scope 1 and 2) emissions but also by indirect exposures embedded in Scope 3 supply chain dependencies (An et al. 2022). Managing CTR, therefore, requires capabilities that extend beyond firm boundaries and static compliance responses, demanding anticipatory, data-intensive and adaptive decision making (Joo et al. 2018).

AI has been widely promoted as a transformative enabler of sustainability, with the potential to improve emissions monitoring, optimise resource allocation and enhance climate-related decision making (Tseng and Lin 2024) as shown in Figure 1. Market projections estimate that AI will reach USD 4.8 trillion by 2033 (UNCTAD 2025), while industry reports suggest that scaling AI applications could mitigate more than 10% of global emissions by 2030 (BCG 2023). Reflecting these expectations, a growing body of academic research shows that AI can enhance the measurement, prediction and disclosure of CTR (Sautner et al. 2023a; Pérez-Pérez et al. 2024) and, in some contexts,

reduce emission intensity or transition exposure by improving efficiency and responsiveness.

Despite these advances, the literature remains theoretically fragmented. Much of it conceptualises AI as either a neutral analytical tool or a firm level capability that complements governance and sustainability controls. These perspectives implicitly assume that improved information, optimisation and efficiency will translate into substantive decarbonisation (Luqman et al. 2024). However, emerging evidence suggests a more ambivalent picture. AI can reinforce short term efficiency gains, generate rebound effects and exacerbate transition risks when decoupled from long term climate objectives (York and McGee 2016; Hahn et al. 2018; Tsolakis et al. 2022). Disclosure-focused studies further caution that improved reporting does not necessarily imply real emissions reductions, particularly when firms engage in symbolic compliance (Lyon and Montgomery 2015; Wang et al. 2025). To move beyond firm centric explanations, recent work has begun to emphasise the importance of AIR, the broader institutional environment that enables or constrains AI adoption (Chishti et al. 2024). AIR encompasses national digital infrastructure, human capital, regulatory quality, innovation capacity and supporting institutions (OECD 2025b; Oxford Insights 2023). In principle, high AIR should provide firms with the external scaffolding to integrate AI into sustainability strategies, including Scope 1–3 emissions monitoring, predictive analytics and compliance with emerging climate disclosure regimes (Gao et al. 2025). From this perspective, firms embedded

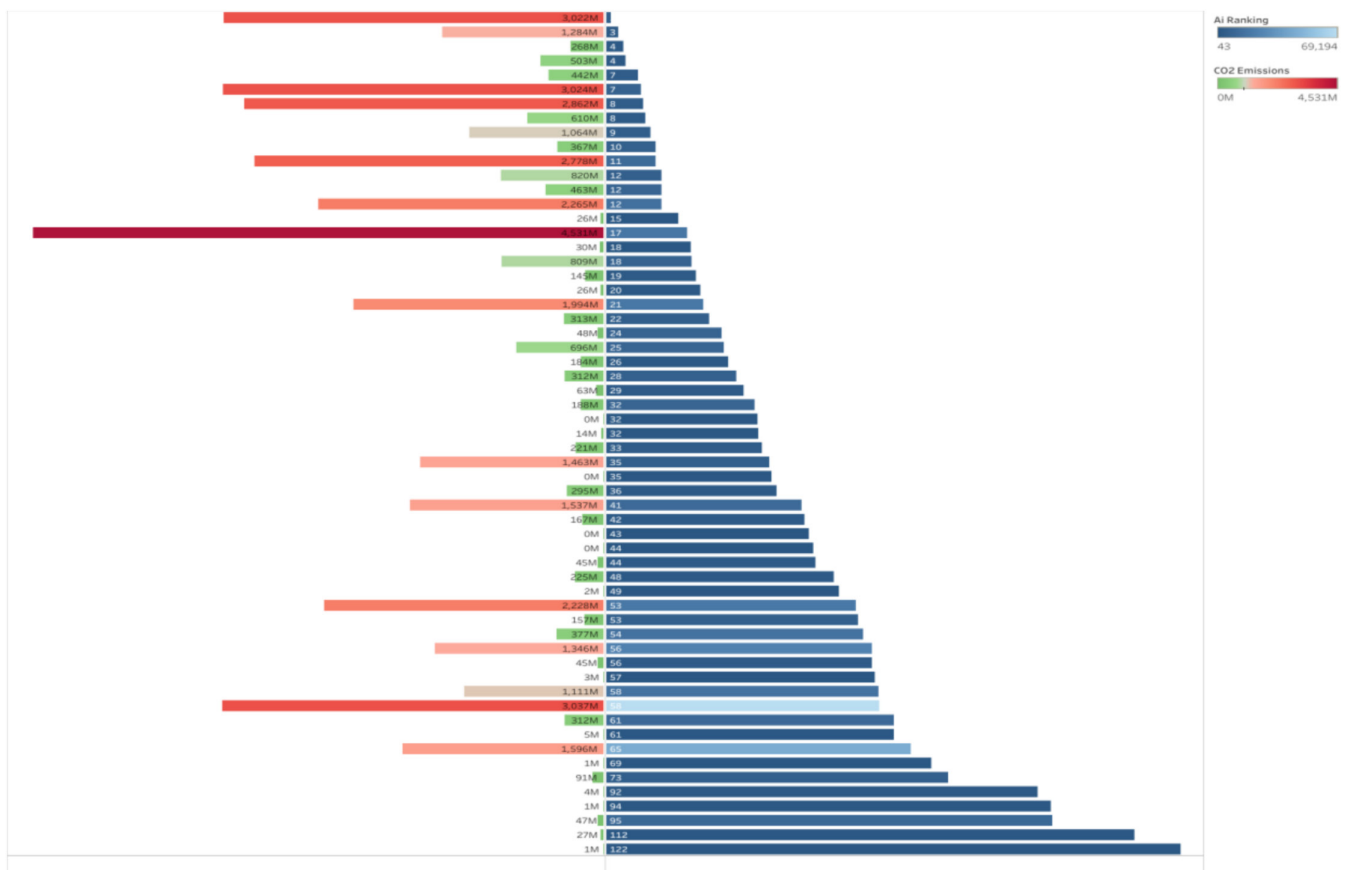


FIGURE 1 | AI ranking and carbon transition risks (Source: Authors (2025)).

in AI-ready environments should be better positioned to anticipate regulatory change, manage supply chain exposure and reduce CTR.

However, existing research assumes AIR is a universal-enabling condition, overlooking its logic dependent effects (Dwivedi et al. 2021). As summarised in Table 1, prior studies predominantly adopt capability, disclosure or optimisation-based lenses and rarely theorise AI or AIR as macro institutional conditions that shape how sustainability is interpreted and enacted (Ding et al. 2023; Oyewo, 2023; Zhang et al. 2025). Consequently, the literature provides limited insight into whether and under what conditions AIR translates into meaningful reductions in CTR rather than into improved risk measurement or symbolic compliance (Tseng and Lin 2024; Wang et al. 2025). Notwithstanding these limitations, the dominant expectation remains that greater AIR enhances firms' ability to manage transition risks by improving information quality, responsiveness and strategic flexibility. Consistent with this baseline view, we posit that, on average, firms operating in more AI-ready institutional environments should exhibit lower exposure CTR.

H1. *Artificial intelligence readiness (AIR) is negatively associated with firm-level carbon transition risk (CTR).*

2.3 | The Moderating Role of Corporate Governance Mechanisms in the AIR–CTR Relationship

The external institutional environment provides firms with opportunities and constraints for pursuing sustainable practices (Walls et al. 2012; George and Schillebeeckx 2022). National digital infrastructure, regulatory frameworks and innovation ecosystems associated with high AIR enable firms to deploy AI for emissions monitoring, optimisation and climate risk management (Chishti et al. 2024; Shonhe et al. 2024). However, these external conditions do not determine outcomes in and of themselves. How firms interpret and mobilise AIR depends critically on internal governance processes, including decision-making structures, board oversight and incentive systems (Min et al. 2022; Rintala et al. 2022). Corporate governance mechanisms such as boards of directors, sustainability committees and executive compensation schemes play a central role in translating external institutional conditions into organisational action (Velte 2023; Salgado-Criado et al. 2024). Importantly, governance structures are not neutral; they reflect dominant institutional logics that shape organisational priorities and define what constitutes legitimate performance (Ameen et al. 2024). Boards guided by market-oriented logics tend to emphasise efficiency, cost reduction and shareholder value maximisation (Zhang et al. 2025).

In contrast, governance aligned with sustainability or stakeholder logics prioritises long-term legitimacy, environmental responsibility and balancing multiple stakeholder interests (Guix et al. 2025). Governance, therefore, acts as an interpretive filter through which AIR enabled technological opportunities are assessed and enacted (van Giffen and Ludwig 2023). From an institutional logics' perspective, this filtering

role helps explain why the AIR–CTR relationship may be non-linear. When market logics dominate governance, AI is more likely to be deployed for short term optimisation, regulatory compliance and reputational management. While such applications may temporarily reduce reported emissions or improve risk metrics. They also increase the likelihood of rebound effects, whereby efficiency gains enable higher production and consumption, ultimately elevating emissions and CTR (Wang et al. 2023). In these contexts, AIR may intensify rather than mitigate CTR. Conversely, when governance aligns with sustainability or stakeholder logics, AI is more likely to be embedded in long term transition strategies, such as Scope 3 emissions management, climate scenario planning and the integration of decarbonisation objectives into core strategic decisions. Here, governance translates AIR into practices consistent with substantive carbon transition.

Crucially, integrating a signalling perspective clarifies how governance loses its disciplining role in high AIR environments. Under conditions of information asymmetry, firms face strong incentives to signal environmental responsibility to regulators, investors and stakeholders (Spence 1973; Connelly et al. 2011; Forcadell et al. 2023). In AI ready contexts, digital sophistication itself becomes a powerful and credible signal. Governance mechanisms such as sustainability committees, AI enabled dashboards and formal policies can therefore be repurposed as signals of compliance and technological competence rather than as constraints on carbon intensive behaviour (Sariyer et al. 2024). When governance is market oriented, these signals substitute for substantive decarbonisation, allowing firms to secure legitimacy through visibility rather than emissions reduction.

Empirical evidence on governance and sustainability outcomes supports this contingency. While some studies find positive effects of governance on environmental performance (Haque and Ntim 2022), others report neutral or negative relationships. Orazalin et al. (2024) show that specific governance structures are associated with higher GHG emissions, suggesting a prioritisation of financial performance over environmental transformation. Wahyuningrum et al. (2025) report that board independence may be negatively related to climate disclosure due to risk aversion or cost minimisation. These mixed findings indicate that governance effectiveness is contingent on the logics it embodies and the signals it prioritises. In high-AIR environments, firms may also face intensified institutional pressure to adopt AI rapidly to demonstrate innovation leadership and regulatory alignment (Organisation for Economic Co-operation and Development (OECD) 2025a). Where market logics dominate governance, this pressure can lead firms to deploy AI primarily for carbon accounting, reporting and optimisation without altering underlying production systems. Such signalling-driven adoption risks locking firms into carbon-intensive trajectories and masking structural vulnerabilities, thereby increasing CTR (Di Chiacchio et al. 2025). This dynamic reflects a sustainability paradox (Hahn et al. 2018), in which technological readiness expands the capacity to signal responsibility while constraining substantive change. It therefore implies that corporate governance should not be viewed as an inherently positive moderator of the AIR–CTR relationship. Instead, its effect

TABLE 1 | AI, corporate governance and carbon transition risk literature:

Article	Focus	Main findings	Theoretical lens used	Gaps
Ding et al. (2023)	AI and carbon emissions reduction.	AI reduces CEs through the spatial spillover effect, with the effect being stronger in central and western China.	None identified uses Dublin model.	Presuming alignment between AI and carbon emissions neglects logic dominance, abstraction and strategic buffering enabled by advanced AI environments.
Oyewo (2023)	Corporate governance and carbon emissions.	Negative link between corporate governance and carbon emissions.	Stakeholder legitimacy theory.	Shows that carbon emission accounting is a strategy for demonstrating transparency and gaining legitimacy but fails to account for conflicting logics in digitally enabled environments.
Sautner et al. (2023a)	M-based firm level climate exposure measures.	Climate transition exposure is priced and predicts innovation responses.	Asset pricing/information economics	Measures exposure, not governance enactment; ignores how national digital institutions condition governance effectiveness.
Wang et al. (2023)	AI and climate risk disclosure quality.	AI improves climate risk disclosure and transparency.	Voluntary disclosure/legitimacy theory (implicit).	Equates disclosure with reduced risk; does not examine decoupling or symbolic compliance enabled by AI under strong governance structure.
Luqman et al. (2024)	AI use in corporate carbon neutrality strategies.	AI supports monitoring, reporting and some decarbonisation initiatives.	Stakeholder theory.	Does not account for institutional context or competing logics; it overlooks how AI may crowd out governance effectiveness in high AIR settings.
Pérez-Pérez et al. (2024)	AI prediction of the financial impacts of climate transition risk.	AI improves the accuracy of transition risk prediction and assessment	Decision theory.	Treats AI as a neutral tool; ignores how AI changes the meaning, interpretation and enactment of risk under governance and climate policies.
Tseng and Lin (2024)	AI and carbon cost reduction.	AI contributes to cost reduction in firms	No identified theory	Fails to acknowledge the institutional environment and possible conflicting logics.
Wang et al. (2025)	Digital intelligence and low carbon transition.	Digital intelligence significantly reduces transition risk through efficiency and information advantages.	Resource based view and dynamic capability	Assumes AI capability complements governance; does not theorise how AI reconfigures institutional logics and weakens governance discipline in high AIR environments.
Zhang et al. (2025)	AI-based measurement of climate policy transition risk.	AI accurately measures firm level transition risk.	Measurement/computational social science.	Focuses on risk quantification rather than strategic behaviour; lacks theorisation of governance and reinterpretation of logic under high AIR.

depends on whether governance mechanisms function primarily as disciplinary constraints aligned with sustainability logics or as signalling devices aligned with market-oriented legitimacy demands.

H2. *Corporate governance mechanisms moderate the relationship between AI readiness (AIR) and carbon transition risk (CTR) such that, when market-oriented logics and signalling incentives dominate governance, the risk-mitigating effect of AIR is weakened or reversed.*

2.4 | The Moderating Role of Internal Climate Policies in the AIR–CTR Relationship

Although AIR creates a favourable external environment for firms pursuing sustainability, the effectiveness of CTR mitigation ultimately depends on how firms internalise these external conditions through organisational structures and practices. Internal climate policies constitute formalised commitments that embed environmental objectives into corporate strategy and decision making (Pan and Lin 2025). These include mechanisms such as internal emissions trading schemes and climate-related incentive systems that allocate resources, shape managerial behaviour and translate abstract sustainability goals into operational routines (Aldy and Gianfrate 2019; Hong et al. 2022; Ren et al. 2024). In principle, such policies move firms beyond regulatory compliance towards proactive climate governance by linking emissions reduction to economic incentives and strategic priorities.

Internal climate policies can play a critical role in bridging AIR with substantive decarbonisation. By providing organisational structures for setting emissions targets, allocating investment capital and rewarding low carbon initiatives, these policies enable firms to mobilise AI enabled data, analytics and forecasting tools towards transition objectives. For example, firms can combine open climate data and AI based analytics to inform emissions targets, capital budgeting and scenario planning, thereby reducing exposure to regulatory shocks and carbon price volatility. In this sense, internal climate policies should enhance firms' capacity to convert national level AIR into effective CTR mitigation strategies (Hossain et al. 2023). However, an institutional logics perspective suggests that the effectiveness of internal climate policies is not automatic. These policies operate within pluralistic institutional environments characterised by competing state, market and environmental logics. While environmental logic frames internal climate policies as mechanisms of accountability and stewardship, market logic emphasises efficiency, cost control and financial performance. Internal climate policies thus serve as arenas in which these competing logics are negotiated and enacted (George and Schillebeeckx 2022).

Integrating a signalling perspective further clarifies why internal climate policies may lose effectiveness in high AIR contexts. In settings with advanced digital capabilities, sustainability is more often measured by clear indicators such as carbon accounting powered by AI, predictive analytics and established climate policies (Yang and Huang 2022; Zhang et al. 2025). These tools can serve as credible signals

of sustainability, conveying commitment and compliance to regulators, investors and stakeholders amid information asymmetries. When internal climate policies are embedded in governance structures dominated by market-oriented logics, their primary function may shift from disciplining emissions-intensive behaviour to legitimising firms through demonstrable digital sophistication (Baldini et al. 2018). In such cases, AI-enabled climate policies support reporting, benchmarking and optimisation without driving substantive changes in production systems. This dynamic creates the possibility of techno-environmental decoupling. Internal climate policies remain formally intact, but their substantive role is diluted as they are repurposed to justify AI investments, meet disclosure requirements or signal alignment with national digital and climate strategies. Rather than constraining carbon-intensive practices, these policies may facilitate symbolic compliance, mask persistent transition vulnerabilities and delay structural transformation (Christensen et al. 2021). As a result, firms may appear climate ready while remaining exposed to underlying CTR. It therefore implies that internal climate policies should not be viewed as uniformly strengthening the AIR–CTR relationship. Instead, their interactions depend on whether they function as substantive governance mechanisms aligned with environmental logics or as signalling devices aligned with market-oriented legitimacy demands. In high AIR environments where signalling pressures are strong, internal climate policies may weaken or even reverse the risk-mitigating effect of AI readiness by prioritising visibility and optimisation over decarbonisation. A summary of our hypotheses development and construction of variables is presented in Figure 2.

H3. *Internal climate policies moderate the relationship between AI readiness (AIR) and carbon transition risk (CTR) such that, in high AIR environments dominated by market-oriented logics and signalling incentives, the risk-mitigating effect of AIR is weakened or reversed.*

3 | Data and Methodology

3.1 | Sample and Data Sources

Our panel dataset of nonfinancial firms is based on the carbon emissions data in the Asset4 ESG (now Refinitiv ESG) database. We then integrate the carbon emissions data with firm-level accounting information from the Refinitiv DataStream/World scope database. The country AI readiness scores come from Oxford Insights and start in the year 2020. Therefore, we restrict our sample to 2020–2023. Finally, we derived country governance indicators and macroeconomic variables from the World Bank's World Development Indicators (WDI) database. After merging all the datasets from Refinitiv ESG, DataStream/World scope, World Bank and Oxford Insights, we removed firm-year observations with missing data on carbon emissions and firm-level financial data. Consistent with prior studies (Luo and Tang 2021; Orazalin et al. 2024), we excluded financial firms because they operate under different accounting requirements, governance systems and regulatory environments. The resulting final sample comprises 8181 firm-level observations from 5363 unique firms across 43 countries for the period 2020–2023. The sample is an

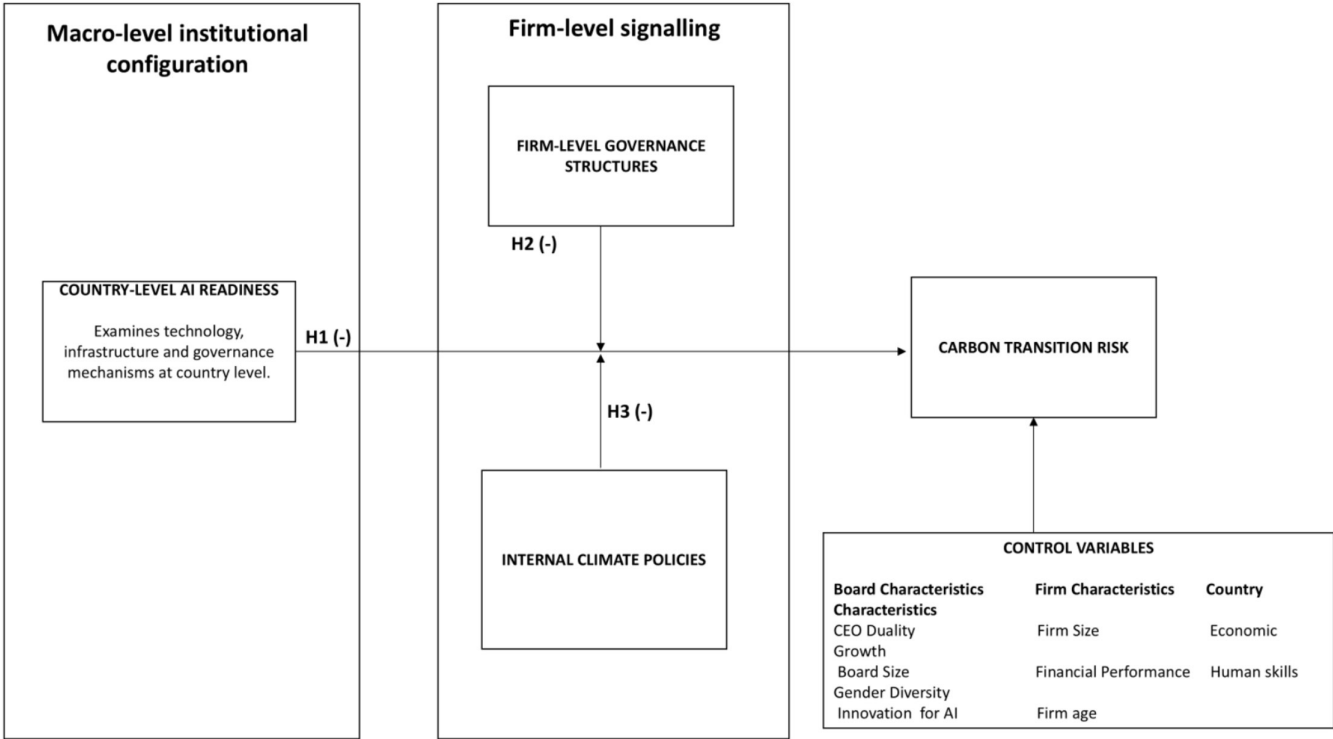


FIGURE 2 | Conceptual framework.

unbalanced panel, reflecting variation in firms' ESG reporting coverage across years rather than attrition driven by the variables of interest.

3.2 | Variable Definitions

3.2.1 | Carbon Transition Risks

Our primary measure of corporate carbon transition risk uses a firm's carbon emissions data, sourced from the Asset4 ESG database, now integrated into the Refinitiv ESG platform. Refinitiv ESG is among the most comprehensive providers of firm level ESG data and is widely used in the corporate sustainability literature. We follow prior studies and measure firm level CTR as the natural logarithm of total GHG emissions (CTR), including direct (Scope 1) (CTR_DIR) and indirect (Scope 2) (CTR_INDIR) emissions (Haque and Ntim 2020; Bolton and Kacperczyk 2023b; Bai and Ru 2024; Orazalin et al. 2024).¹ Asset4 ESG distinguishes direct emissions from sources owned and controlled by the company and indirect emissions arising from the generation of imported (purchased) electricity, heat or steam consumed by the company.²³ Thus, the total carbon emissions measure is comprehensive, encompassing direct and indirect emissions attributable to a company. Similar to prior studies, we perform robustness analyses using Scope 1 direct emissions and Scope 2 indirect emissions as alternative measures of CTR (Konadu et al. 2022; Oyewo 2023). Finally, higher values indicate greater GHG emissions, weaker carbon performance and higher CTR (Moussa et al. 2020; Bolton and Kacperczyk 2023b; Orazalin et al. 2024).

3.2.2 | Artificial Intelligence Readiness

Country level AIR data are sourced from Oxford Insights,⁴ which publishes the annual Government AIR index—a composite measure that assesses a country's capacity to integrate AI into the delivery of public services and to support broader economic transformation. The overall AIR_Score is constructed from three equally weighted composite pillars: AIR Government (AIR_Govt), which captures institutional capacity and regulatory preparedness; AIR Technology Sector (AIR_Tech), which reflects the maturity and density of the domestic technology ecosystem; and AIR Data and Infrastructure (AIR_Infr), which assesses the quality and accessibility of data systems and digital infrastructure. Prior studies argue that firms can leverage AI driven technologies to achieve decarbonisation through energy transitions and cost efficiencies (Ding et al. 2023; Tao et al. 2024). Using a country level measure is appropriate here because the regulatory, infrastructural and institutional conditions that enable firm level AI adoption are primarily determined at the national level, and firm level AI adoption data with sufficient coverage across our 43-country sample for this period.

3.2.3 | Moderating Variables

To test hypothesis 2 (H2), we moderate the relationship between AIR and CTR with a firm's corporate governance quality. We measure corporate governance using Refinitiv ESG's overall corporate governance pillar score (GOV), which reflects how board members and executives adopt best management practices to maximise shareholder value. Related studies

(e.g., Hussain et al. 2018; Orazalin et al. 2024; Oyewo 2023) measure a firm's corporate governance using CEO-Chair duality (*CEO_CHAIR*), board size (*BODSIZE*), board independence (*BODIND*), board gender diversity (*BODDIV*) and the number of board meetings (*BODMEET*), which are documented to influence corporate carbon emissions and, hence, CTR. Moreover, we include ESG-based compensation (*ESG_COMP*) and emissions trading (*ENV_COMM*) as corporate governance indicators that may influence a firm's carbon emissions risks (Oyewo 2023). We examine how corporate governance moderates the effects of AIR on a firm's CTR by interacting each measure with the AIR score.

We also test hypothesis 3 (H3) by moderating the AIR with variables measuring a firm's internal climate change policy. We measure a firm's internal climate policy using the following three variables: climate incentive (*CLIM_INC*) and emissions trading (*EM_TRG*). Hong et al. (2022) find that emissions trading improves energy efficiency. Albitar et al. (2023) find that corporate climate incentives and environmental commitments via commitments significantly enhance a firm's climate change commitments. Moreover, Bolton and Kacperczyk (2023a) argue that firms that make concrete commitments reduce their carbon emissions and CTR. However, they also find that firm commitments to reducing carbon emissions are more prevalent in countries without national obligations. In other words, firms' internal commitments to mitigate CTR substitute for the absence of obligations by the domiciled countries. Therefore, the effects of a firm's internal climate policy on CTR should be more pronounced when AIR is low.

3.2.4 | Control Variables

We also include several control variables to account for confounding effects from firm and country specific characteristics that may affect AIR Score and CTR. Consistent with prior studies (e.g., Bolton and Kacperczyk 2023b; Orazalin et al. 2024), we control for firm level variables such as firm size (*SIZE*), market-to-book ratio (*MB*), leverage (*LEV*), cash holdings (*CASH*), profitability (*ROA*), a dummy variable for dividend-paying firms (*DIVD*), capital expenditure (*CAPEX*), research and development expenses (*R&D*), firm age (*LOGAGE*) and closed-held shares (*SHARES*). Furthermore, we follow the literature (e.g., Jia et al. 2019; Ding et al. 2022; Ma and Hao 2022; Agyei-Boapeah et al. 2024) and include country level variables that capture the macroeconomic and institutional characteristics of the home country, such as GDP growth rate (*GDP growth*), a country's human development index (*HDI*) and a measure of governance quality (*WGI*), inflation and the extent of globalisation (*GLOBALISED*). Finally, we include dummy variables to control for year, industry and country specific effects.

3.3 | Empirical Model

To test our first hypothesis, examining the direct impact of AI readiness on corporate carbon transition risk, we estimate the following baseline regression:

$$CTR_{i,t} = \beta_0 + \beta_1 AIR_{c,t} + \beta_2 CONTROLS_{i,t,c} + \text{Year FE} + \text{Industry FE} + \text{Country FE} + \varepsilon_{i,t} \quad (1)$$

where i , c and t index firm, country and year, respectively. The dependent variable is the natural logarithm of a firm's total carbon emissions, which we use as a proxy for corporate CTR. Taking the natural logarithm addresses the well documented right skewness of raw emissions distributions and yields a semi-elasticity interpretation for the coefficients. *AIR* is the Oxford Insights country level AIR Score assigned to firm i based on its country of domicile in year t . *CONTROLS* is a vector of firm level and country level variables drawn from the World Bank's World Development Indicators. *Year FE*, *Industry FE* and *Country FE* are the year, industry and country specific effects. Table 2 summarises the descriptive statistics for the variables used in the regression.

Although we refer to this as an OLS regression, the inclusion of *Year*, *Industry* and *Country* fixed effects means the model is estimated by the within-group OLS transformation, absorbing all time invariant country level unobservable that correlate with a country's AI readiness measure, all industry specific regulatory and technological characteristics correlated with emissions intensity, and common macroeconomic shocks that affect all firms in a given year. This three-way fixed effect's structure is chosen over firm fixed effects for an important reason: AIR is measured at the country level and varies across countries and years but not across firms within the same country-year cell. A firm-fixed-effects estimator would absorb all between country variation in AI readiness, rendering the coefficient on AIR unidentified. Country fixed effects instead control for time invariant cross-country heterogeneity while preserving the cross-sectional and over time variation in AIR that identifies our estimates. To assess the appropriateness of the fixed-effects specification, we conduct a Hausman test comparing fixed and random-effects estimators. The test results support the use of fixed effects as the preferred specification (see Appendix D).

4 | Findings and Implications

4.1 | Baseline Effect: AIR and CTR

We examined how AIR relates to CTR using a logic sensitive approach. According to the results shown in Table 3 for Equation 1, there is a statistically significant negative relationship between AIR and CTR ($\beta = -4.671$, $p < 0.001$). This implies that firms operating in environments well prepared for AI tend to face substantially less CTR. The evidence aligns with Hypothesis 1 and echoes previous studies indicating that AI based analytics, forecasting and integrated data systems improve firms' ability to foresee and handle climate related challenges (Sautner et al. 2023b; Pérez-Pérez et al. 2024). It is important to note that these results should not be misconstrued as evidence that AI adoption alone reduces CTR. Consistent with the literature synthesis presented in Table 1, the findings indicate that the associated benefits of AI extend beyond technological capabilities at the firm level to broader institutional ecosystems in which AI operates. Thus, AIR serves as a macro level facilitator, influencing firms' access to interoperable data infrastructures, a skilled workforce and legitimised approaches to AI implementation (Dunz et al.

TABLE 2 | Descriptive statistics.

Variables	<i>n</i>	Mean	SD	Min	Median	Max
<i>CTR</i>	8181	12.013	2.591	0.000	12.099	19.424
<i>CTR_DIR</i>	7496	11.015	3.066	0.000	11.075	19.365
<i>CTR_INDIR</i>	7512	10.963	2.545	0.000	11.194	17.562
<i>AIR_SCORE</i>	8181	0.740	0.102	0.366	0.764	0.882
<i>AIR_TECH</i>	8181	0.618	0.117	0.256	0.624	0.833
<i>AIR_GOVT</i>	8181	0.764	0.133	0.317	0.804	0.949
<i>AIR_INFR</i>	8181	0.838	0.092	0.470	0.858	0.945
<i>GOV</i>	8181	0.650	0.191	0.067	0.676	0.995
<i>CEOCHAIR</i>	8181	0.295	0.456	0.000	0.000	1.000
<i>BODSIZE</i>	8181	10.412	3.681	3.000	10.000	98.000
<i>BODIND</i>	8181	0.625	0.236	0.000	0.625	1.000
<i>BODDIV</i>	8181	0.296	0.140	0.000	0.300	0.750
<i>BODMEET</i>	8181	10.145	5.749	1.000	9.000	154.000
<i>ESG_COMP</i>	8181	0.594	0.491	0.000	1.000	1.000
<i>ENV_COMM</i>	8181	0.869	0.337	0.000	1.000	1.000
<i>SIZE</i>	8181	16.646	2.387	10.959	16.316	26.769
<i>MB</i>	8181	2.173	2.109	0.341	1.428	29.179
<i>LEV</i>	8181	0.201	0.159	0.000	0.164	0.922
<i>CASH</i>	8181	0.117	0.094	0.000	0.093	0.817
<i>ROA</i>	8181	0.076	0.073	−0.338	0.069	0.316
<i>DIVD</i>	8181	0.745	0.436	0.000	1.000	1.000
<i>CAPEX</i>	8181	0.037	0.032	0.000	0.028	0.411
<i>R&D</i>	8181	0.028	0.060	0.000	0.002	0.878
<i>FIRMAGE</i>	8181	20.910	13.336	1.000	20.000	58.000
<i>SHARES</i>	8181	10.101	2.927	0.000	10.399	18.853
<i>GDP</i>	8181	0.009	0.056	−0.113	0.026	0.136
<i>WGI</i>	8181	0.216	2.070	−5.811	0.625	2.641
<i>INFL</i>	8181	0.032	0.033	0.000	0.024	0.290
<i>HDI</i>	8181	0.641	0.038	0.490	0.654	0.674
#Firms: 5363						

Note: This table presents the descriptive statistics for the firm-level and country-level variables utilised in the regression models. Appendix A provides the variable definitions.

2021). In this capacity, AIR establishes the structural, cognitive and normative foundations to successfully align digital transformation initiatives with decarbonisation goals.

This baseline effect reflects the combined influence of state, market and environmental logics in coherent institutional environments. State logic manifests through national digital strategies, public investment in AI infrastructure and data governance frameworks that collectively lower adoption barriers

and confer legitimacy on AI as an instrument of climate action (GPAI 2024; Organisation for Economic Co-operation and Development (OECD) 2025a). These institutional arrangements enhance firms' capacity to identify emission hotspots, model transition scenarios and anticipate regulatory change, thereby reducing exposure to abrupt policy shocks, asset revaluation and carbon price volatility. In this respect, AIR serves as a policy transmission mechanism, translating national decarbonisation objectives into organisational-level

TABLE 3 | AI readiness and carbon transition risks.

Variables	CTR		CTR_DIR		CTR_INDIR	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>AIR_SCORE</i>	−4.671*** (−3.011)	−4.706** (−2.362)	−4.777** (−2.542)	−4.938** (−2.048)	−0.550 (−0.301)	3.923 (1.630)
<i>GOV</i>	0.520*** (5.098)	0.526*** (5.160)	0.467*** (3.577)	0.469*** (3.583)	0.603*** (4.851)	0.602*** (4.846)
<i>CEOCHAIR</i>	0.006 (0.149)	0.005 (0.120)	0.047 (0.919)	0.046 (0.896)	−0.020 (−0.414)	−0.019 (−0.382)
<i>BODSIZE</i>	0.489*** (6.637)	0.488*** (6.630)	0.284*** (3.033)	0.284*** (3.035)	0.484*** (5.091)	0.482*** (5.084)
<i>BODIND</i>	0.086 (0.934)	0.084 (0.910)	−0.196* (−1.683)	−0.196* (−1.689)	0.069 (0.589)	0.072 (0.620)
<i>BODDIV</i>	−0.200 (−1.251)	−0.209 (−1.308)	−0.313 (−1.559)	−0.315 (−1.567)	−0.187 (−0.924)	−0.183 (−0.906)
<i>BODMEET</i>	−0.322*** (−6.972)	−0.323*** (−6.988)	−0.307*** (−5.415)	−0.309*** (−5.428)	−0.359*** (−6.158)	−0.366*** (−6.294)
<i>ESG_COMP</i>	−0.028 (−0.747)	−0.029 (−0.752)	−0.011 (−0.234)	−0.011 (−0.228)	−0.042 (−0.880)	−0.038 (−0.790)
<i>ENV_COMM</i>	0.323*** (5.879)	0.327*** (5.958)	0.428*** (5.888)	0.430*** (5.921)	0.148** (2.310)	0.150** (2.344)
<i>SIZE</i>	0.898*** (50.198)	0.897*** (50.226)	1.000*** (47.877)	0.999*** (47.831)	0.909*** (49.442)	0.910*** (49.661)
<i>MB</i>	−0.101*** (−9.265)	−0.101*** (−9.221)	−0.144*** (−10.277)	−0.144*** (−10.266)	−0.067*** (−5.372)	−0.067*** (−5.338)
<i>LEV</i>	0.902*** (6.011)	0.916*** (6.084)	1.025*** (5.510)	1.031*** (5.527)	−0.125 (−0.696)	−0.122 (−0.675)
<i>CASH</i>	−0.580*** (−2.831)	−0.579*** (−2.826)	−0.607** (−2.312)	−0.606** (−2.308)	−0.852*** (−3.442)	−0.874*** (−3.526)
<i>ROA</i>	1.467*** (4.950)	1.460*** (4.922)	0.658* (1.653)	0.659* (1.655)	0.971** (2.511)	1.009*** (2.623)
<i>DIVD</i>	−0.019 (−0.438)	−0.016 (−0.371)	0.001 (0.020)	0.003 (0.049)	0.049 (0.955)	0.041 (0.810)
<i>CAPEX</i>	14.049*** (16.701)	14.038*** (16.706)	16.799*** (16.270)	16.803*** (16.276)	8.290*** (7.968)	8.301*** (7.981)
<i>R&D</i>	−3.677*** (−9.677)	−3.666*** (−9.632)	−4.182*** (−7.746)	−4.172*** (−7.714)	−2.916*** (−6.981)	−2.901*** (−6.907)
<i>FIRMAGE</i>	0.081*** (3.935)	0.081*** (3.931)	0.136*** (5.281)	0.136*** (5.269)	0.104*** (3.999)	0.103*** (3.992)

(Continues)

TABLE 3 | (Continued)

Variables	CTR		CTR_DIR		CTR_INDIR	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>SHARES</i>	0.029*** (4.214)	0.029*** (4.282)	0.028*** (3.285)	0.028*** (3.298)	−0.002 (−0.221)	−0.002 (−0.235)
<i>GDP</i>		1.156 (1.185)		1.075 (0.896)		−2.643** (−2.045)
<i>WGI</i>		−0.446* (−1.701)		−0.175 (−0.530)		−0.741** (−2.401)
<i>INFL</i>		0.899 (0.573)		0.437 (0.238)		−5.384*** (−2.798)
<i>HDI</i>		−6.867 (−0.498)		−3.109 (−0.181)		12.919 (0.804)
Constant	−1.419 (−1.209)	3.072 (0.356)	−3.651** (−2.573)	−1.520 (−0.141)	−4.940*** (−3.523)	−16.151 (−1.608)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8181	8181	7496	7496	7512	7512
Adjusted R^2	0.730	0.730	0.720	0.719	0.620	0.621

Note: This table presents the OLS regression results of AI readiness (*AIR*) and carbon transition risks (*CTR*). Appendix A provides the variable definitions. The t values are in parentheses.

*, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

risk management capabilities. However, this transmission is neither automatic nor uniform; it depends on how firms interpret and operationalise institutional signals within their governance structures.

Market logic further reinforces the baseline *AIR*–*CTR* relationship in digitally advanced economies, where AI enabled efficiency gains, predictive maintenance and emissions forecasting are integrated into performance optimisation strategies (Vasilescu et al. 2025). When sustainability objectives are embedded within strategic and financial decision making, AI reframes environmental responsibility from a compliance obligation into a source of competitive advantage. This alignment can reduce firms' vulnerability to investor scrutiny and regulatory uncertainty, thereby lowering *CTR*. Although these patterns resemble results from capability-based research showing that increased efficiency lowers emissions intensity and reduces transition risks (Wang et al. 2023; Fu et al. 2024), our study goes further by revealing that such advantages depend on comprehensive institutional alignment, not just technological capabilities.

Environmental and stakeholder logics provide an additional normative layer that can stabilise the risk reducing effect of *AIR* (Fu et al. 2024). In institutional contexts where AI is explicitly

framed as a tool for ethical, transparent and low carbon innovation, firms face heightened expectations for accountability and credible climate action (Srivastava et al. 2025). AI-powered monitoring and reporting systems can enhance traceability and data reliability, reducing opportunities for opportunistic disclosure and strengthening reputational legitimacy. Crucially, however, this contrasts with disclosure-oriented research, which cautions that improvements in reporting quality do not necessarily translate into substantive reductions in emissions (Lyon and Montgomery 2015; Wang et al. 2023). This conflict underscores that AI-enabled transparency mitigates transition risk only when supported by aligned institutional logics; in its absence, it may merely obscure underlying vulnerabilities.

Our findings, therefore, imply that *AIR* is associated with lower *CTR* only under conditions of institutional coherence, where divergent logics mutually reinforce one another. Under such conditions, *AIR* is characterised as a transformational institutional capability that simultaneously supports economic performance and decarbonisation. However, this relationship is inherently fragile. As the interaction effects reveal, once governance arrangements privilege techno-market priorities over sustainability logics, the stabilising role of *AIR* erodes. Thus, the baseline *AIR*–*CTR* relationship should be understood not as a universal effect, but as a conditional outcome

TABLE 4 | Firm-level governance, AI readiness and carbon transition risks.

Variables	CTR (1)	CTR_DIR (2)	CTR_ INDIR (3)
<i>AIR_SCORE</i>	−6.340*** (−3.054)	−5.995** (−2.373)	−0.119 (−0.047)
<i>GOV</i>	−1.171* (−1.896)	−0.626 (−0.798)	−3.584*** (−4.956)
<i>AIR_ SCORE×GOV</i>	2.320*** (2.780)	1.495 (1.415)	5.728*** (5.884)
<i>CEOCHAIR</i>	0.008 (0.206)	0.048 (0.932)	−0.010 (−0.205)
<i>BODSIZE</i>	0.487*** (6.641)	0.283*** (3.025)	0.479*** (5.097)
<i>BODIND</i>	0.076 (0.822)	−0.202* (−1.739)	0.052 (0.450)
<i>BODDIV</i>	−0.212 (−1.324)	−0.314 (−1.562)	−0.181 (−0.896)
<i>BODMEET</i>	−0.324*** (−7.002)	−0.310*** (−5.449)	−0.370*** (−6.374)
<i>ESG_COMP</i>	−0.030 (−0.793)	−0.012 (−0.252)	−0.041 (−0.855)
<i>ENV_COMM</i>	0.324*** (5.904)	0.428*** (5.890)	0.140** (2.208)
<i>SIZE</i>	0.896*** (50.255)	0.999*** (47.858)	0.908*** (49.731)
<i>MB</i>	−0.099*** (−9.094)	−0.143*** (−10.225)	−0.064*** (−5.160)
<i>LEV</i>	0.904*** (5.966)	1.022*** (5.453)	−0.164 (−0.901)
<i>CASH</i>	−0.587*** (−2.867)	−0.611** (−2.328)	−0.898*** (−3.626)
<i>ROA</i>	1.440*** (4.856)	0.648 (1.626)	0.958** (2.495)
<i>DIVD</i>	−0.023 (−0.522)	−0.001 (−0.026)	0.024 (0.464)
<i>CAPEX</i>	14.002*** (16.679)	16.774*** (16.235)	8.189*** (7.886)
<i>R&D</i>	−3.650*** (−9.586)	−4.163*** (−7.697)	−2.862*** (−6.785)

(Continues)

TABLE 4 | (Continued)

Variables	CTR (1)	CTR_DIR (2)	CTR_ INDIR (3)
<i>FIRMAGE</i>	0.079*** (3.847)	0.135*** (5.234)	0.099*** (3.848)
<i>SHARES</i>	0.029*** (4.301)	0.028*** (3.292)	−0.002 (−0.270)
<i>GDP</i>	1.187 (1.219)	1.088 (0.908)	−2.599** (−2.014)
<i>WGI</i>	−0.456* (−1.739)	−0.181 (−0.547)	−0.760** (−2.480)
<i>INFL</i>	1.032 (0.659)	0.491 (0.268)	−5.179*** (−2.706)
<i>HDI</i>	−6.876 (−0.501)	−3.153 (−0.184)	12.689 (0.793)
Constant	4.302 (0.499)	−0.694 (−0.064)	−12.963 (−1.296)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Observations	8181	7496	7512
Adjusted R^2	0.730	0.720	0.623

Note: This table presents the OLS regression results of the interaction between AI readiness and corporate governance on carbon transition risks. Appendix A provides the variable definitions. The t values are in parentheses.

*, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

that depends critically on how institutional logics are aligned and enacted within firms.

4.2 | Firm Level Governance, AIR and CTR

As presented in Table 4, our findings indicate that although corporate governance mechanisms are independently associated with lower CTR ($\beta = -1.171$, $p < 0.01$), the interaction between AIR and corporate governance is positive and statistically significant ($\beta = 2.320$, $p < 0.001$). It indicates that in highly AI ready environments, stronger governance mechanisms attenuate or reverse the risk reducing effect of AIR. This interaction reflects a shift in the dominance of logic in digitally advanced contexts. As AIR increases, state and market logics become increasingly salient, privileging technological sophistication, data governance and efficiency-focused performance metrics. In such environments, governance mechanisms, rather than mediating between competing logics, begin to reinforce a techno-market paradigm in which AI adoption itself becomes a signal of legitimacy, independent of its environmental impact (Di Chiacchio et al. 2025).

Boards may prioritise AI-driven cost savings, algorithmic efficiency and data governance under the assumption that these will, in turn, deliver sustainability outcomes. However, this reorientation weakens the translation of AIR into substantive decarbonisation. Instead, governance structures may facilitate institutional decoupling, where firms signal alignment with climate agendas while maintaining carbon-intensive practices (Delmas and Burbano 2011). In this sense, governance acts as a constraint rather than a conduit for transition, enabling disclosure, reputational management or efficiency gains without altering underlying emissions trajectories. These dynamics are consistent with greenwashing behaviours (Seele and Schultz 2022; Albitar et al. 2023) and with rebound effects associated with efficiency-driven resource use (Alcott 2005; Naz et al. 2024).

Additionally, Figure 3 of the marginal effects plots shows that the moderating effect of governance quality is economically meaningful. At lower levels of governance quality, AI readiness has a stronger negative impact on total CTR, implying that AI systems compensate for weak internal corporate governance. However, as governance quality improves, the incremental contribution of AIR to CTR reduction diminishes because stronger governance mechanisms already perform some of these monitoring and control functions.

4.3 | Internal Climate Policy, AIR and CTR

A comparable trend is observed for internal climate policies, as shown in Table 5. Although these policies are independently associated with reduced CTR, reflecting their environmental rationale and ethical responsibility (Aldy and Gianfrate 2019; Hong et al. 2022), the interaction between AIR and internal

climate policies shows a positive, statistically significant relationship ($\beta = 0.703$, $p < 0.001$). It suggests that in AI-ready environments, the effectiveness of internal climate policies in mitigating CTR diminishes. This situation illustrates a process of techno-environmental decoupling. In environments with high AIR, state driven initiatives (such as national AI strategies and digital competitiveness agendas) and market imperatives (including demands for efficiency and innovation) increasingly shape organisational priorities (GPAI 2024; Organisation for Economic Co-operation and Development (OECD) 2025; Vasilescu et al. 2025).

Consequently, while internal climate policies remain formally in place, they are often reinterpreted primarily as tools to legitimise AI investments rather than as mechanisms explicitly designed to reduce emissions. Climate policies may thus become performative, supporting AI enabled accounting, reporting and compliance rather than substantive mitigation (Dunz et al. 2021; Di Chiacchio et al. 2025). This dilutes the normative force of environmental logic and increases the likelihood of symbolic compliance (Christensen et al. 2021). In such settings, AIR amplifies transition risk by shifting organisational focus towards technological signalling rather than reducing carbon intensity.

Figures 4 and 5 support the argument that internal climate incentives and emissions trading are less effective at reducing CTR for firms operating in higher AIR environments. The chart provides visual support for the argument that internal climate incentives are less effective at reducing CTR for firms with higher AIR. Across the three panels, the marginal effects of AIR remain negative for both overall CTR and direct CTR (CTR_DIR), indicating that AI capability generally reduces carbon transition exposure. However, the effects are less

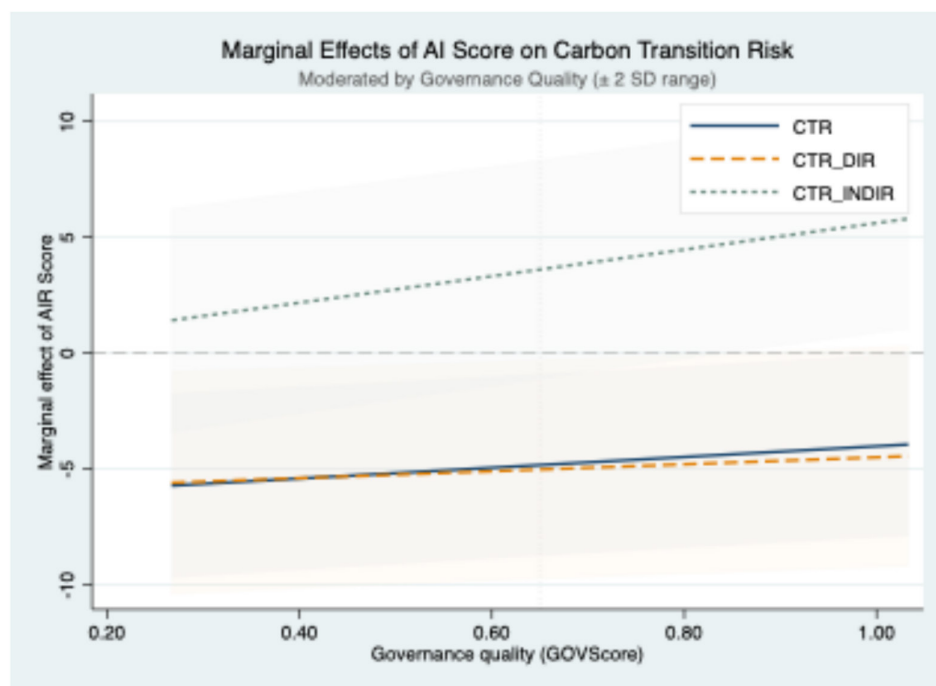


FIGURE 3 | Marginal effect plots moderated by governance quality (GOV).

TABLE 5 | Internal climate policy, AI readiness and carbon transition risks.

Variables	CTR		CTR_DIR		CTR_INDIR	
	(1)	(2)	(3)	(4)	(5)	(6)
AIR_SCORE	−5.002** (−2.508)	−4.899** (−2.486)	−5.313** (−2.201)	−4.977** (−2.087)	3.743 (1.548)	3.563 (1.483)
CLIM_INC	−0.444* (−1.694)		−0.350 (−1.062)		−0.593* (−1.763)	
AIR_SCORE×CLIM_INC	0.703** (2.035)		0.695 (1.586)		0.739* (1.671)	
EM_TRG		−0.779** (−2.339)		−0.334 (−0.895)		−1.565*** (−4.130)
AIR_SCORE×EM_TRG		1.675*** (3.716)		1.194** (2.357)		2.375*** (4.708)
GOV	0.474*** (4.534)	0.481*** (4.728)	0.355*** (2.617)	0.418*** (3.193)	0.633*** (4.994)	0.577*** (4.666)
CEOCHAIR	0.003 (0.085)	0.003 (0.065)	0.040 (0.767)	0.041 (0.798)	−0.017 (−0.337)	−0.015 (−0.303)
BODSIZE	0.484*** (6.600)	0.447*** (6.209)	0.274*** (2.931)	0.237*** (2.586)	0.490*** (5.172)	0.467*** (4.918)
BODIND	0.092 (0.995)	0.057 (0.618)	−0.183 (−1.564)	−0.233** (−2.009)	0.071 (0.609)	0.069 (0.594)
BODDIV	−0.200 (−1.251)	−0.177 (−1.113)	−0.295 (−1.468)	−0.244 (−1.222)	−0.186 (−0.921)	−0.181 (−0.896)
BODMEET	−0.325*** (−7.043)	−0.306*** (−6.659)	−0.313*** (−5.516)	−0.291*** (−5.152)	−0.365*** (−6.274)	−0.348*** (−5.959)
ESG_COMP	−0.056 (−1.428)	−0.040 (−1.060)	−0.067 (−1.310)	−0.023 (−0.472)	−0.027 (−0.534)	−0.046 (−0.955)
ENV_COMM	0.331*** (6.028)	0.315*** (5.779)	0.442*** (6.069)	0.413*** (5.697)	0.144** (2.252)	0.145** (2.279)
SIZE	0.894*** (49.837)	0.863*** (47.379)	0.994*** (47.414)	0.956*** (44.647)	0.909*** (49.170)	0.893*** (47.188)
MB	−0.101*** (−9.313)	−0.105*** (−9.522)	−0.145*** (−10.437)	−0.149*** (−10.648)	−0.067*** (−5.363)	−0.068*** (−5.459)
LEV	0.906*** (6.020)	0.927*** (6.183)	1.017*** (5.451)	1.058*** (5.691)	−0.122 (−0.677)	−0.106 (−0.589)
CASH	−0.585*** (−2.855)	−0.664*** (−3.227)	−0.623** (−2.368)	−0.699*** (−2.650)	−0.869*** (−3.502)	−0.925*** (−3.714)

(Continues)

TABLE 5 | (Continued)

Variables	CTR		CTR_DIR		CTR_INDIR	
	(1)	(2)	(3)	(4)	(5)	(6)
ROA	1.490*** (5.025)	1.518*** (5.127)	0.714* (1.789)	0.762* (1.924)	1.033*** (2.679)	1.010*** (2.633)
DIVD	−0.020 (−0.460)	−0.009 (−0.198)	−0.001 (−0.023)	0.011 (0.203)	0.035 (0.690)	0.051 (0.999)
CAPEX	14.060*** (16.748)	13.828*** (16.289)	16.818*** (16.322)	16.599*** (16.153)	8.333*** (8.012)	8.183*** (7.881)
R&D	−3.650*** (−9.592)	−3.651*** (−9.549)	−4.141*** (−7.674)	−4.134*** (−7.617)	−2.891*** (−6.890)	−2.891*** (−6.890)
FIRMAGE	0.082*** (3.955)	0.084*** (4.098)	0.136*** (5.283)	0.139*** (5.457)	0.104*** (4.015)	0.103*** (3.996)
SHARES	0.029*** (4.301)	0.032*** (4.796)	0.028*** (3.300)	0.033*** (3.898)	−0.002 (−0.215)	−0.001 (−0.096)
GDP	1.121 (1.150)	1.392 (1.433)	1.030 (0.860)	1.305 (1.093)	−2.669** (−2.064)	−2.538** (−1.963)
WGI	−0.475* (−1.809)	−0.379 (−1.457)	−0.200 (−0.603)	−0.112 (−0.340)	−0.773** (−2.494)	−0.701** (−2.277)
INFL	1.013 (0.648)	0.970 (0.632)	0.609 (0.333)	0.437 (0.244)	−5.401*** (−2.795)	−5.278*** (−2.748)
HDI	−7.046 (−0.512)	−8.097 (−0.593)	−2.372 (−0.138)	−4.963 (−0.290)	11.420 (0.707)	12.625 (0.797)
Constant	3.481 (0.403)	4.563 (0.534)	−1.570 (−0.146)	0.394 (0.037)	−15.065 (−1.492)	−15.452 (−1.560)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8173	8173	7486	7486	7502	7502
Adjusted R ²	0.800	0.801	0.797	0.798	0.679	0.680

Note: This table presents the OLS regression results of the interaction between AI readiness and internal climate policy on carbon transition risks. Appendix A provides the variable definitions. The *t* values are in parentheses.

*, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

negative when climate incentives and emissions trading are present (“Yes = 1”) than when they are absent (“No = 0”). This pattern suggests that the risk reducing impact of AI weakens in firms operating with internal climate incentives and emissions trading.

Our findings, therefore, suggest a paradoxical logic. AIR is associated with lower CTR on average. However, its risk mitigating potential erodes and may even reverse when dominant techno-market logics subsume governance mechanisms and internal climate policies. Rather than reinforcing sustainability,

governance and policy instruments may be repurposed as signals of digital and regulatory conformity, weakening their disciplining role. These results help explain why prior studies report conflicting effects of governance on environmental outcomes (Yang and Huang, 2022; Dunz et al. 2021; Pan and Li 2025) governance is not inherently pro- or anti sustainability, but contingent on the institutional logics it enacts. AIR therefore operates as a double-edged institutional condition, enabling decarbonisation when logics are aligned, but amplifying transition risk when technological readiness outpaces normative and governance alignment.

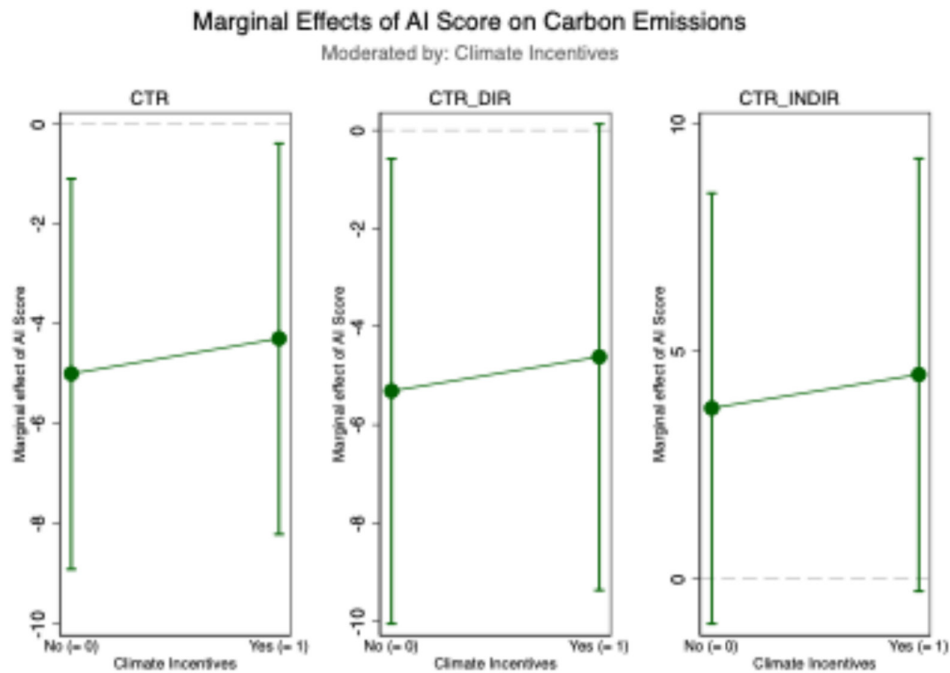


FIGURE 4 | Marginal effect plots moderated by climate incentives.

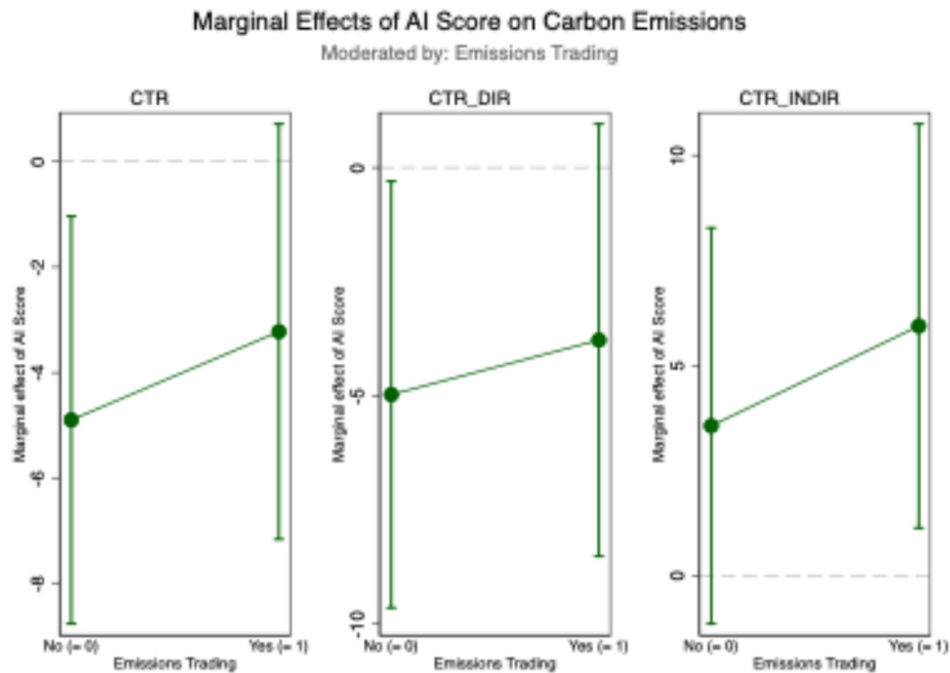


FIGURE 5 | Marginal effect plots moderated by emissions trading.

5 | Conclusion and Implications

5.1 | Summary, Limitations and Future Research

Using panel data on 5363 focal enterprises across 43 countries between 2020 and 2023, we examined the relationship between AIR and CTR through a logic-sensitive lens. This approach provided a deeper understanding of how the alignment/conflict among competing logics influenced the extent to which AI readiness translates into effective decarbonisation

outcomes. We show that AIR can improve firms' digital capacity to address decarbonisation challenges. However, its effectiveness ultimately depends on how organisations interpret, negotiate and align competing institutional logics, especially those originating from the state, market and environmental domains. Misalignment of logics often leads firms to prioritise efficiency and profitability over environmental commitments. This may lead to the use of AI ready environments for profitability rather than for decarbonisation, thereby intensifying CTR.

Our findings offer insight into why firms with similar technology capabilities may experience different climate outcomes by emphasising how AIR functions as an institutional field with embedded technological, regulatory and normative expectations. We extend the boundaries of sustainability and digital transformation research by highlighting institutional coherence and governance hybridity as critical enablers of meaningful, rather than symbolic, AI powered climate action. We also advance institutional logics theory by demonstrating that the efficacy of technological readiness depends not only on digital capacity but also on institutional alignment and the interpretive reconciliation of state, market and environmental logics.

Furthermore, we demonstrate that the future of AI-enabled decarbonisation extends beyond technological advancement to encompass institutional alignment (the harmonisation of national and corporate governance systems). Embedding these alignments across firms could facilitate steering verifiable carbon transition outcomes through functional institutional capability. Our findings also have policy implications, as they highlight the importance of strengthening the complementarity between conflicting logics (state, market and environmental) that drive the governance of AI enabled sustainability. The state logic offers legitimacy and regulatory guidance, but it frequently prioritises technical adoption over accountability for outcomes. Policymakers should therefore go beyond digital capacity building to establish climate accountability measures, such as enforcing third party certification of internal climate policy and connecting AI innovation funding to verifiable emissions outcomes. This integration connects the coercive and normative components of the state logic with environmental imperatives, preventing AIR from becoming a tool for symbolic compliance.

Regulators can reduce rebound effects that counteract market driven sustainability benefits by combining AI driven efficiency regulations with market corrective tools and AI specific ESG transparency requirements. This would ensure that profitability is balanced by processes that internalise environmental costs, resulting in a more synergistic link between market and environmental logics. Boards and CEOs should develop hybrid governance capabilities that are technologically literate, environmentally mindful and institutionally reflexive, to combat organisations' ability to internalise these norms. Their interpretive capacity and governance orientation influence their capacity to do so. Such governance redesigns help reconcile tensions between profitability, regulatory conformity and environmental integrity, transforming AIR into a legitimate and effective catalyst for low carbon innovation rather than a symbolic or compliance-driven artefact.

Like any research, our study has several limitations that provide avenues for future research. First, while panel data enable temporal inference, the three-year window (2020–2023) may not fully capture long term institutional or regulatory shifts. Future research could extend the timeframe to explore how evolving states and environmental logics reshape the AIR–CTR relationship over time. In addition, although AIR indices at the country level are reliable for cross national comparisons, they may obscure notable intra-country and sectoral variations in institutional coherence. Future studies could use multilevel designs to examine how industry level sustainability standards or the

quality of subnational governance affect the level of institutional alignment.

Furthermore, while we draw on institutional logics in this study, we do not directly measure stakeholder perceptions, board-level logics negotiation or AI governance maturity at the firm level. The use of a qualitative or mixed-methods approach in future research could provide a more in-depth understanding of how organisational actors interpret and enact institutional pressures within their digital transformation and climate strategies. Finally, this study's focus on focal firms may limit the understanding of how AIR diffuses through value chains. Future studies could investigate supply chain ecosystems and SMEs, where institutional logics are experienced differently due to asymmetric resource access and governance dependence. Comparative analyses across industries and institutional regimes could further illustrate the boundary conditions under which AIR functions as a genuine institutional enabler rather than a symbolic artefact of sustainability discourse.

5.2 | Implications of Findings

5.2.1 | Theoretical Implications

Existing research suggests that AI and digital capabilities can improve emissions reduction, transition risk assessment, disclosure quality and low carbon performance through efficiency, monitoring and information advantages (Ding et al. 2023; Luqman et al. 2024; Wang et al. 2025). However, these studies largely assume that digital capabilities and governance are inherently complementary in supporting sustainability outcomes. Our findings challenge this assumption by theorising AIR as an institutional condition that reshapes governance enactment and conditions whether digital readiness supports substantive decarbonisation or legitimises carbon-intensive continuity. More specifically, we extend institutional perspectives on sustainability by reconceptualising AIR as a macro institutional condition that shapes how firms interpret and respond to CTR. By integrating signalling theory, we further show that AIR heightens the salience of visible and credible sustainability signals such as AI enabled disclosures, dashboards and formal governance structures, thereby extending how sustainability is enacted to include evaluation and legitimisation.

We also challenge capability-based and governance complementarity assumptions in AI and sustainability research by theorising the AIR governance relationship as contingent and potentially contradictory. In doing so, we move beyond linear assumptions of AI as inherently sustainability-enhancing and develop a more contingent theory of AI-enabled sustainability governance. We extend institutional logics theory by introducing signalling substitution as a mechanism to explain why sustainability governance may remain formally strong yet substantively weak in digitally advanced contexts. We show that high AIR environments can privilege techno-economic logics that recast governance mechanisms and climate policies as signals of compliance and digital competence rather than constraints on carbon intensive behaviour. This demonstrates that digitalisation does not merely introduce another competing logic but can

reorder the hierarchy of logics by privileging those generating observable and legitimating signals.

5.2.2 | Practical Implications

This study offers important practical implications for managers, boards, investors and policymakers navigating CTR in increasingly digitalised institutional environments. A central implication is that AI-ready environments do not automatically translate into substantive decarbonisation. While AI-enabled analytics enhance risk sensing, scenario modelling and forecasting (Mikalef et al. 2021), they also expand managerial discretion by enabling firms to manage and signal transition risk without addressing its structural drivers. Managers should therefore treat AI as a strategic amplifier rather than a standalone solution, explicitly linking AI-enabled insights to operational decarbonisation, capital reallocation and asset-level transformation rather than to reporting and optimisation alone.

Traditional governance signals, such as climate committees or AI-powered dashboards, may signal sustainability legitimacy but not real action. Boards should assess not just the presence of AI systems and climate policies, but also their actual impact, and require better digital literacy to ensure AI risk assessments drive tangible changes in operations and investments. Without this scrutiny, governance risks support only superficial compliance. Internal climate policies must also be designed to remain effective amid heightened digital and signalling complexity. Policies centred on targets, disclosure and compliance are particularly vulnerable to being reinterpreted as performative signals in AI-ready environments. Firms should therefore complement these policies with hard constraints such as mandatory capital expenditure reviews, process redesign requirements or supply chain interventions when AI identifies persistent transition risks. Embedding climate objectives within cross-functional decision-making structures, rather than confining them to sustainability units, can further reduce the risk that climate policies become decoupled from core operations.

For investors and financial market actors, the findings caution against equating digital sophistication and governance strength with lower transition risk. In AI ready environments, strong governance structures and advanced analytics may primarily serve as signals of compliance and technological competence, masking underlying exposure. Investors should therefore triangulate AI related disclosures with observable indicators of transformation, including emissions trajectories, asset retirement decisions and capital allocation towards low carbon technologies.

Finally, for policymakers, the results underscore the need for logic- and signalling-sensitive regulation. While national investments in AI infrastructure enhance firms' analytical capacity, they may also unintentionally amplify symbolic compliance if regulatory frameworks focus solely on reporting and technological adoption. Policymakers should therefore ensure that digitalisation strategies are complemented by regulatory mechanisms that tie AI-enabled reporting and analytics to verifiable operational change, such as performance-based standards, asset-level disclosures and enforcement linked to emissions outcomes rather than process sophistication.

Author Contributions

Emilia Vann Yaroson: conceptualization; investigation; validation; visualization; project administration; resources; writing – original draft; writing – review and editing. **Daniel Gymiah:** methodology; data curation; investigation; validation; formal analysis; visualization. **Syed Imran Ali:** validation; writing – original draft; writing – review and editing. **Mélanie Roux:** writing – original draft. **Amelie Abadie:** writing – original draft. **Christian Gnekpe:** writing – review and editing. All authors contributed to the interpretation of findings, critically reviewed the manuscript and approved the final version for publication.

Disclosure

The authors used AI-assisted tools solely for clarity, grammar and phrasing improvements. No AI was used to generate new scholarly content, ideas or arguments.

Endnotes

¹ ASSET 4 ESG computes the total emissions value from the GHG Protocol as the sum of direct (Scope 1) and indirect (Scope 2) emissions. According to ASSET 4 ESG, the GHG Protocol takes priority over the others when the company reports CO₂ and CO₂ equivalent emissions according to various protocols (ex: GHG Protocol, Kyoto Protocol, EU Trading Scheme).

² Direct (Scope 1) emissions come from sources owned or controlled by the reporting company. These emissions come from the following sources: the generation of intermediate energy, transportation/business travel where the transportation methods are owned by the company, operations of buildings and the sale of own-generated electricity to another company.

³ Indirect emissions reported under Scope 2 arise from generating imported (purchased) electricity, heat or steam the organisation consumes. ASSET 4 ESG excludes emissions reported under Scope 3 of the GHG Protocol as these emissions are not controlled or owned by the company, and it does not influence them. Moreover, Scope 3 emissions reporting is optional as it is very difficult to compute and full of estimates.

⁴ Each AI Readiness pillar is constructed from corresponding dimensions: The dimensions of AI Readiness Government are Vision, Governance and Ethics, Digital Capacity and Adaptability; the dimensions of the AI Readiness Technology Sector are Size, Innovation Capacity and Human Capital; and AI Readiness Data and Infrastructure are Infrastructure, Data Availability and Data Representativeness. <https://oxfordinsights.com/ai-readiness/ai-readiness-index/>.

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Appendix A: Definitions of Variables

Variable	Notation	Definition	Source
Carbon transition risks	<i>CTR</i>	The natural logarithm of total greenhouse gas (GHG) emissions (<i>CTR</i>), including direct (Scope 1) (<i>CTR_DIR</i>) and indirect (Scope 2) (<i>CTR_INDIR</i>) emissions.	Refinitiv ESG
Artificial Intelligence Readiness	<i>AIR_SCORE</i>	A measure of a country's overall integration of AI in delivering public services (<i>AIR_Score</i>). This <i>AIR_Score</i> is derived from three composite measures (pillars): AI Readiness Government (<i>AIR_Govt</i>), AI Readiness Technology Sector (<i>AIR_Tech</i>) and AI Readiness Data and Infrastructure (<i>AIR_Infr</i>).	Oxford Insights
Climate incentives	<i>CLIM_INC</i>	A dummy variable is if a company provides climate incentives.	Refinitiv ESG
Emissions trading	<i>EM_TRG</i>	A dummy variable if the company participates in any emissions trading initiative.	Refinitiv ESG
Corporate governance	<i>GOV</i>	A firm's overall measure of corporate governance quality.	Refinitiv ESG
CEO-Chair duality	<i>CEOCHAIR</i>	A dummy variable equals 1 if the CEO is also the board chair and 0 otherwise.	Refinitiv ESG
Board size	<i>BODSIZE</i>	Number of board members.	Refinitiv ESG
Board independence	<i>BODIND</i>	The proportion of independent directors on the board.	Refinitiv ESG
Board diversity	<i>BODDIV</i>	Percentage of female board members.	Refinitiv ESG
Board meetings	<i>BODMEET</i>	Number of board meetings.	Refinitiv ESG
ESG-related compensation	<i>ESG_COMP</i>	A dummy variable is if a firm has an ESG-related compensation policy.	Refinitiv ESG
Emission trading	<i>ENV_COMM</i>	A dummy variable is if a firm has an emission trading.	Refinitiv ESG
Firm size	<i>SIZE</i>	The natural logarithm of total assets	Worldscope
Return on assets	<i>ROA</i>	Net income divided by total assets.	Worldscope
Market-to-book ratio	<i>MB</i>	The ratio of the market value of equity to the book value of equity.	Worldscope
Leverage	<i>LEV</i>	The ratio of total debt to total assets.	Worldscope
Cash holdings	<i>CASH</i>	Cash and cash equivalents scaled by total assets.	Worldscope
Capital expenditure	<i>CAPEX</i>	The ratio of capital expenditure to total assets.	Worldscope
Research and development expenses	<i>R&D</i>	The ratio of research and development expenditure to total assets.	Worldscope
Firm age	<i>FIRMAGE</i>	The natural logarithm of the age of the firm.	Worldscope
Closely held shares	<i>SHARES</i>	The percentage of shares is closely held.	Worldscope
GDP growth rate	<i>GDP</i>	GDP growth rate of a firm's headquartered country.	World Bank
World Governance Index	<i>WGI</i>	The first principal component of the six dimensions of a country's governance: Voice and Accountability, Political Stability and Absence of Violence/Terrorism, Government Effectiveness, Regulatory Quality, Rule of Law and Control of Corruption	World Bank
Inflation rate	<i>INFL</i>	The annual change in the consumer price index.	World Bank
Human Development Index	<i>HDI</i>	A measure of average achievement in key dimensions of human development: a long and healthy life, knowledge and decent living standards.	UNDP

Appendix B: Correlation Matrix

	Variables	1	2	3	4	5	6	7	8	9	10	11	12
1	CTR	1.000											
2	AIR_SCORE	−0.160***	1.000										
3	GOV	0.167***	0.107***	1.000									
4	CEOCHAIR	0.058***	0.091***	−0.154***	1.000								
5	BODSIZE	0.337***	−0.074***	0.047***	0.135***	1.000							
6	BODIND	−0.020*	0.307***	0.324***	−0.018	−0.143***	1.000						
7	BODDIV	−0.095***	0.149***	0.250***	0.046***	0.104***	0.200***	1.000					
8	BODMEET	−0.041***	−0.007	0.033***	−0.069***	−0.063***	−0.023**	0.012	1.000				
9	ESG_COMP	0.118***	−0.010	0.319***	−0.006	0.142***	0.165***	0.327***	−0.014	1.000			
10	ENV_COMM	0.185***	−0.049***	0.234***	−0.006	0.167***	0.034***	0.119***	0.017	0.194***	1.000		
11	SIZE	0.503***	−0.237***	0.085***	0.021*	0.254***	−0.201***	−0.275***	0.048***	−0.106***	0.102***	1.000	
12	MB	−0.320***	0.115***	−0.049***	0.030***	−0.130***	0.039***	0.028**	−0.074***	−0.059***	−0.117***	−0.174***	1.000
13	LEV	0.298***	−0.168***	−0.006	0.016	0.196***	−0.060***	−0.058***	0.094***	0.069***	0.087***	0.174***	−0.474***
14	CASH	−0.267***	0.018	−0.056***	0.022**	−0.095***	−0.024**	−0.020*	0.013	−0.053***	−0.093***	−0.171***	0.257***
15	ROA	−0.014	−0.027**	0.052***	0.013	−0.098***	0.053***	−0.006	−0.121***	0.017	−0.003	−0.009	0.440***
16	DIVD	0.216***	−0.111***	0.051***	0.055***	0.105***	−0.086***	−0.055***	−0.056***	0.002	0.051***	0.236***	−0.016
17	CAPEX	0.252***	−0.135***	−0.055***	−0.006	−0.020*	−0.037***	−0.118***	−0.002	0.024**	0.014	0.033***	0.029***
18	R&D	−0.223***	0.170***	0.030***	0.038***	−0.020*	0.088***	0.024**	−0.045***	−0.042***	−0.011	−0.060***	0.297***
19	FIRMAGE	0.139***	0.094***	0.061***	0.084***	0.045***	0.063***	−0.049***	−0.017	−0.008	0.036***	0.132***	−0.073***
20	SHARES	0.188***	−0.307***	−0.094***	−0.008	0.115***	−0.350***	−0.124***	0.083***	−0.048***	0.041***	0.337***	−0.069***
21	GDP	−0.017	0.071***	0.075***	−0.014	−0.072***	0.018	−0.006	−0.065***	0.028**	0.040***	0.004	0.070***
22	WGI	−0.213***	0.610***	0.139***	−0.091***	−0.099***	0.229***	0.295***	0.053***	0.139***	0.023**	−0.276***	0.056***
23	INFL	0.049***	−0.247***	−0.017	−0.070***	−0.037***	−0.036***	−0.065***	−0.081***	−0.043***	0.061***	0.069***	−0.031***
24	HDI	−0.199***	0.713***	0.135***	0.005	−0.058***	0.204***	0.233***	0.087***	0.130***	−0.008	−0.315***	0.040***
	Variables	13	14	15	16	17	18	19	20	21	22	23	24
14	CASH	−0.232***	1.000										
15	ROA	−0.403***	0.093***	1.000									
16	DIVD	−0.096***	−0.132***	0.249***	1.000								
17	CAPEX	0.008	−0.107***	0.173***	0.080***	1.000							
18	R&D	−0.234***	0.197***	−0.028**	−0.108***	−0.109***	1.000						
19	FIRMAGE	−0.018*	−0.060***	0.033***	0.129***	0.005	−0.004	1.000					
20	SHARES	0.144***	−0.005	−0.016	0.100***	0.052***	−0.083***	−0.066***	1.000				
21	GDP	−0.095***	−0.016	0.138***	0.047***	−0.005	0.012	0.007	0.028**	1.000			
22	WGI	−0.151***	−0.040***	−0.036***	−0.049***	−0.110***	0.110***	−0.024**	−0.276***	−0.042***	1.000		
23	INFL	0.049***	−0.024**	0.107***	0.014	0.074***	−0.071***	−0.034***	0.121***	0.184***	−0.275***	1.000	
24	HDI	−0.103***	0.004	−0.061***	−0.063***	−0.110***	0.127***	−0.011	−0.307***	−0.029***	0.878***	−0.251***	1.000

Note: This table presents the pairwise correlation matrix for the dependent, test and control variables. Appendix A provides the variable definitions.

*, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

Appendix C: AIR Components and CTR

Variables	CTR			CTR_DIR			CTR_INDIR		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<i>AIR_Tech</i>	−0.050 (−0.031)			−1.325 (−0.695)			4.429** (2.311)		
<i>AIR_Govt</i>		−5.040*** (−4.372)			−2.967** (−2.226)			−1.244 (−0.937)	
<i>AIR_INFR</i>			0.131 (0.151)			−0.716 (−0.651)			1.598 (1.592)
<i>GOV</i>	0.518*** (5.099)	0.520*** (5.118)	0.518*** (5.081)	0.460*** (3.523)	0.462*** (3.537)	0.463*** (3.541)	0.609*** (4.908)	0.609*** (4.912)	0.601*** (4.839)
<i>CEOCHAIR</i>	0.004 (0.091)	0.003 (0.076)	0.004 (0.089)	0.045 (0.875)	0.045 (0.865)	0.045 (0.875)	−0.019 (−0.392)	−0.018 (−0.363)	−0.019 (−0.378)
<i>BODSIZE</i>	0.485*** (6.584)	0.493*** (6.689)	0.485*** (6.586)	0.281*** (3.003)	0.287*** (3.061)	0.280*** (2.994)	0.483*** (5.093)	0.488*** (5.134)	0.486*** (5.120)
<i>BODIND</i>	0.083 (0.900)	0.081 (0.881)	0.083 (0.899)	−0.196* (−1.682)	−0.198* (−1.699)	−0.197* (−1.691)	0.069 (0.595)	0.072 (0.619)	0.073 (0.625)
<i>BODDIV</i>	−0.210 (−1.312)	−0.201 (−1.255)	−0.210 (−1.311)	−0.313 (−1.558)	−0.311 (−1.550)	−0.316 (−1.571)	−0.186 (−0.921)	−0.182 (−0.901)	−0.181 (−0.893)
<i>BODMEET</i>	−0.326*** (−7.031)	−0.326*** (−7.043)	−0.326*** (−7.032)	−0.310*** (−5.443)	−0.310*** (−5.444)	−0.311*** (−5.459)	−0.367*** (−6.295)	−0.364*** (−6.241)	−0.365*** (−6.261)
<i>ESG_COMP</i>	−0.023 (−0.605)	−0.025 (−0.664)	−0.023 (−0.594)	−0.007 (−0.136)	−0.007 (−0.139)	−0.007 (−0.145)	−0.039 (−0.807)	−0.043 (−0.894)	−0.039 (−0.810)
<i>ENV_COMM</i>	0.326*** (5.940)	0.322*** (5.866)	0.326*** (5.943−2)	0.430*** (5.911)	0.427*** (5.876)	0.429*** (5.903)	0.147** (2.307)	0.150** (2.355)	0.150** (2.345)
<i>SIZE</i>	0.897*** (50.099)	0.898*** (50.520)	0.897*** (50.112)	1.000*** (47.808)	1.000*** (47.890)	1.000*** (47.801)	0.909*** (49.675)	0.909*** (49.696)	0.910*** (49.719)
<i>MB</i>	−0.100*** (−9.185)	−0.100*** (−9.205)	−0.100*** (−9.185)	−0.143*** (−10.225)	−0.144*** (−10.235)	−0.144*** (−10.236)	−0.067*** (−5.378)	−0.067*** (−5.368)	−0.067*** (−5.335)
<i>LEV</i>	0.916*** (6.085)	0.907*** (6.039)	0.916*** (6.075)	1.030*** (5.519)	1.026*** (5.497)	1.033*** (5.531)	−0.120 (−0.666)	−0.123 (−0.683)	−0.125 (−0.694)
<i>CASH</i>	−0.590*** (−2.883)	−0.579*** (−2.836)	−0.591*** (−2.884)	−0.616** (−2.346)	−0.612** (−2.332)	−0.610** (−2.322)	−0.861*** (−3.477)	−0.866*** (−3.494)	−0.876*** (−3.530)
<i>ROA</i>	1.460*** (4.918)	1.438*** (4.841)	1.459*** (4.918)	0.660* (1.656)	0.650 (1.630)	0.658* (1.651)	1.002*** (2.603)	1.010*** (2.625)	1.009*** (2.620)
<i>DIVD</i>	−0.015 (−0.330)	−0.016 (−0.367)	−0.015 (−0.329)	0.003 (0.057)	0.003 (0.054)	0.004 (0.069)	0.043 (0.834)	0.040 (0.783)	0.040 (0.789)
<i>CAPEX</i>	14.019*** (16.682)	14.001*** (16.624)	14.017*** (16.670)	16.778*** (16.263)	16.773*** (16.224)	16.780*** (16.261)	8.309*** (7.983)	8.326*** (8.004)	8.304*** (7.984)
<i>R&D</i>	−3.658*** (−9.630)	−3.657*** (−9.644)	−3.657*** (−9.619)	−4.164*** (−7.713)	−4.159*** (−7.713)	−4.164*** (−7.708)	−2.896*** (−6.900)	−2.906*** (−6.928)	−2.901*** (−6.913)
<i>FIRMAge</i>	0.082*** (3.950)	0.081*** (3.912)	0.082*** (3.950)	0.136*** (5.281)	0.136*** (5.266)	0.137*** (5.290)	0.104*** (4.003)	0.103*** (3.968)	0.103*** (3.975)

Variables	CTR			CTR_DIR			CTR_INDIR		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<i>SHARES</i>	0.029*** (4.244)	0.028*** (4.221)	0.029*** (4.241)	0.028*** (3.265)	0.028*** (3.268)	0.028*** (3.300)	−0.001 (−0.163)	−0.002 (−0.227)	−0.002 (−0.267)
<i>GDP</i>	0.357 (0.396)	1.426 (1.490)	0.315 (0.333)	0.145 (0.133)	0.846 (0.726)	0.442 (0.381)	−1.778 (−1.538)	−1.670 (−1.348)	−2.506** (−2.040)
<i>WGI</i>	−0.519** (−1.972)	−1.144*** (−3.748)	−0.541* (−1.848)	−0.243 (−0.736)	−0.614 (−1.638)	−0.125 (−0.331)	−0.682** (−2.236)	−0.840** (−2.382)	−0.952*** (−2.707)
<i>INFL</i>	−1.048 (−0.794)	1.852 (1.200)	−1.121 (−0.856)	−1.371 (−0.899)	0.112 (0.061)	−1.291 (−0.859)	−4.596*** (−2.915)	−3.014 (−1.607)	−4.500*** (−2.845)
<i>HDI</i>	−16.326 (−1.210)	4.490 (0.318)	−16.596 (−1.231)	−12.806 (−0.763)	−0.579 (−0.033)	−11.141 (−0.665)	21.312 (1.359)	25.381 (1.537)	17.353 (1.106)
Constant	5.792 (0.664)	−3.729 (−0.423)	5.833 (0.677)	1.966 (0.181)	−4.413 (−0.399)	0.646 (0.060)	−21.426** (−2.096)	−20.381** (−1.976)	−17.420* (−1.737)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8181	8181	8181	7496	7496	7496	7512	7512	7512
Adjusted R^2	0.730	0.730	0.730	0.719	0.719	0.719	0.621	0.621	0.621

Note: This table presents the OLS regression results of AIR components (*AIR_TECH*, *AIR_GOVT*, *AIR_INFR*) and carbon transition risks (*CTR*). Appendix A provides the variable definitions. The t values are in parentheses.

*, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

Appendix D: Random Effects Estimation

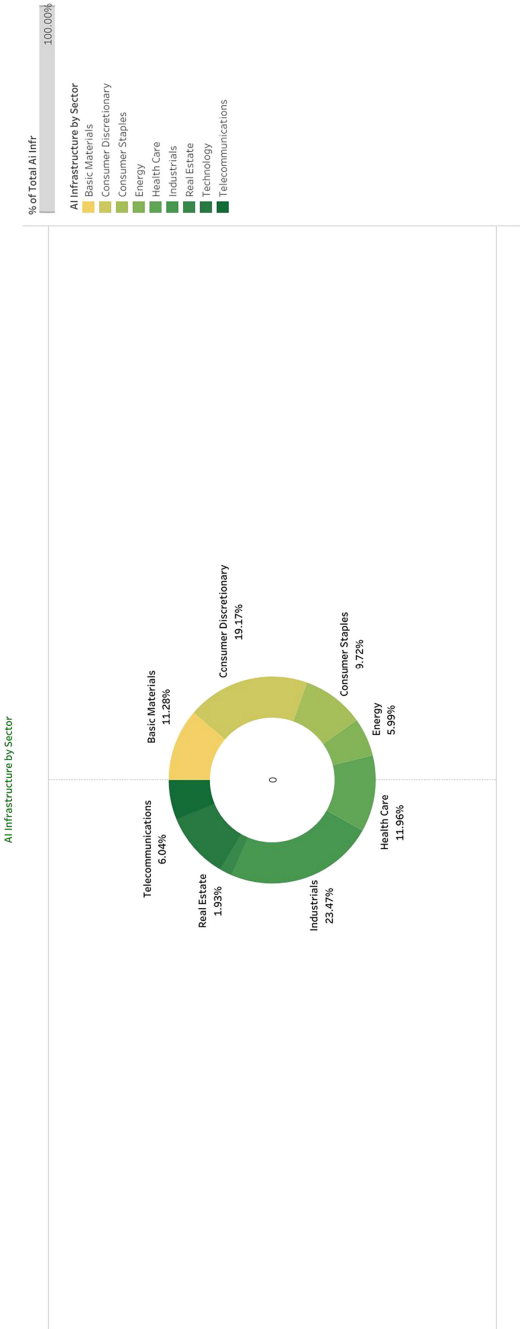
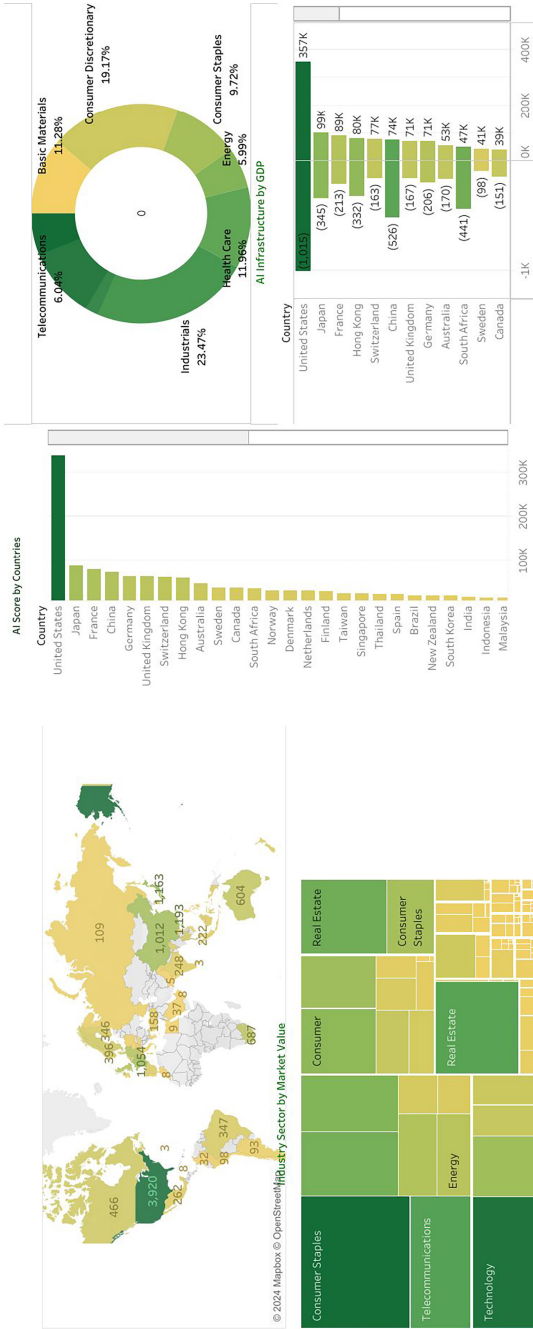
Variables	CTR (1)	CTR_DIR (2)	CTR_INDIRE (3)
<i>AIR_SCORE</i>	−0.107 (0.751)	−0.702* (0.052)	1.600*** (0.000)
<i>GOV</i>	0.383*** (0.002)	0.432*** (0.000)	0.531*** (0.000)
<i>CEOCHAIR</i>	0.093*** (0.005)	0.102*** (0.002)	0.008 (0.879)
<i>BODSIZE</i>	0.715*** (0.000)	0.522*** (0.000)	1.010*** (0.000)
<i>BODIND</i>	0.449*** (0.000)	0.264*** (0.005)	0.498*** (0.000)
<i>BODDIV</i>	0.179 (0.109)	0.244* (0.057)	0.194 (0.245)
<i>BODMEET</i>	−0.078** (0.014)	−0.098*** (0.002)	−0.161*** (0.000)
<i>ESG_COMP</i>	0.149*** (0.000)	0.158*** (0.000)	0.143*** (0.000)
<i>ENV_COMM</i>	0.111** (0.014)	0.051 (0.430)	0.097 (0.142)
<i>SIZE</i>	0.441*** (0.000)	0.461*** (0.000)	0.434*** (0.000)
<i>MB</i>	−0.085*** (0.000)	−0.153*** (0.000)	−0.085*** (0.000)
<i>LEV</i>	1.202*** (0.000)	0.618*** (0.001)	0.439** (0.016)
<i>CASH</i>	−1.422*** (0.000)	−1.135*** (0.000)	−1.621*** (0.000)
<i>ROA</i>	0.791*** (0.000)	0.011 (0.963)	0.705*** (0.007)
<i>DIVD</i>	0.057*** (0.007)	0.053*** (0.004)	0.076** (0.011)
<i>CAPEX</i>	5.610*** (0.000)	4.591*** (0.000)	4.566*** (0.000)
<i>R&D</i>	−5.180*** (0.000)	−5.831*** (0.000)	−2.756*** (0.000)
<i>FIRMAGE</i>	0.123*** (0.000)	0.158*** (0.000)	0.174*** (0.000)
<i>SHARES</i>	−0.004 (0.416)	0.003 (0.569)	−0.026*** (0.000)
<i>GDP</i>	−0.835***	−0.317***	−2.003***

Variables	CTR (1)	CTR_DIR (2)	CTR_INDIRE (3)
	(0.000)	(0.004)	(0.000)
<i>WGI</i>	−0.182*** (0.000)	−0.150*** (0.000)	−0.212*** (0.000)
<i>INFL</i>	−1.869*** (0.000)	−0.863*** (0.008)	−3.416*** (0.000)
<i>HDI</i>	6.108*** (0.000)	7.808*** (0.000)	2.445 (0.107)
Constant	−1.782* (0.076)	−3.050** (0.016)	−1.970** (0.044)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Observations	8181	7496	7512
Hausman <i>p</i>	0.000	0.000	0.000

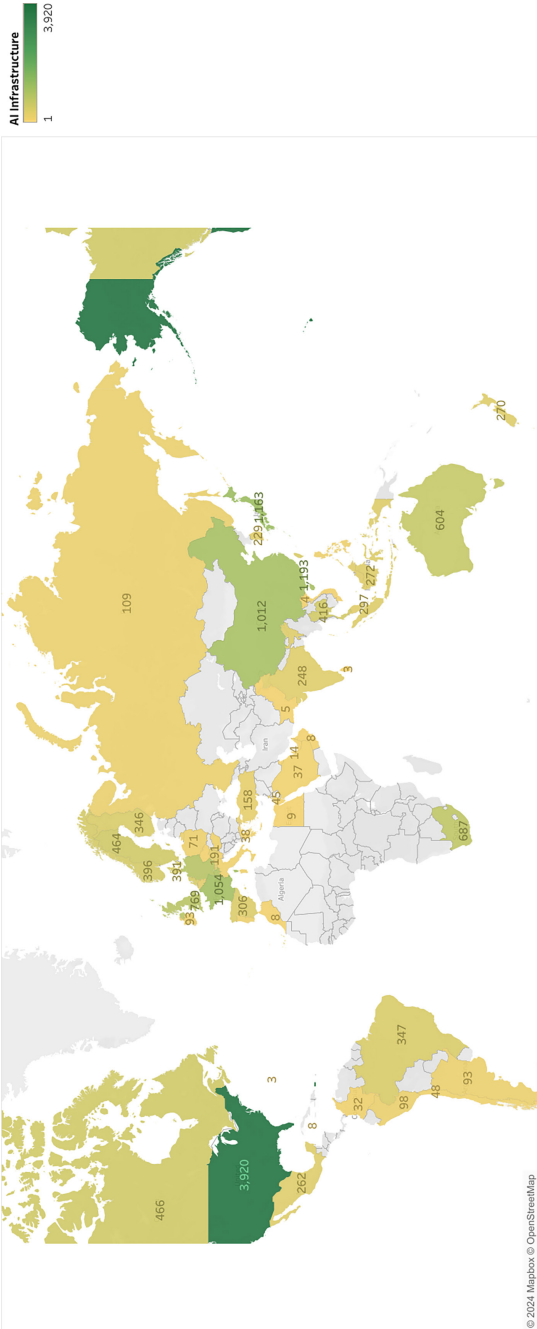
Note: This table presents the OLS regression results of AI readiness (*AIR*) and carbon transition risks (*CTR*). Appendix A provides the variable definitions. The *t* values are in parentheses.

*, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

Appendix E: AI Score by Country and Industry



0 and 0. For pane Sum of 0. Colour shows details about Icbn. Size shows % of Total AI Infr. The marks are labelled by Icbn and % of Total AI Infr. Details are shown for 0.



Biographies

Emilia Vann Yaroson is an assistant professor in operations and supply chain management at the University of Sheffield Management School. Her research lies at the intersection of emerging technologies, digital transformation, supply chain resilience and sustainability, with a particular focus on critical supply chains such as healthcare and pharmaceuticals. She is interested in understanding how technologies including artificial intelligence, blockchain, big data analytics and digital platforms can be governed and deployed responsibly to enhance organisational performance, resilience and sustainable outcomes. Dr. Yaroson's research explores how organisations, governments and healthcare systems can leverage technological innovation to address complex societal and operational challenges, including medicine shortages, healthcare resilience, pharmaceutical supply chain integrity and sustainability transitions. Her work combines rigorous academic inquiry with practical impact, drawing on interdisciplinary perspectives to inform both policy and practice. She has published in leading international journals and actively collaborates with policymakers, industry stakeholders, healthcare organisations and international partners to address pressing challenges relating to AI governance, healthcare systems and critical supply chain resilience. Her research contributes to ongoing debates on the responsible use of technology to support resilient, sustainable and inclusive futures.

Daniel Gyimah is an associate professor in finance at the Ajman University. He holds a PhD in Accounting and Finance from the University of Glasgow, an MSc in Investment Analysis from the University of Stirling and a BCom in Accounting from the University of Cape Coast, Ghana. Dr. Gyimah is a CFA charter holder and a member of the CFA Institute. His research interests focus on corporate finance, including capital structure, dividend policy, share repurchases, trade credit, corporate governance and the influence of peer effects on corporate decision-making. He investigates how financial constraints, investor sentiment, political risk and governance mechanisms affect firms' financial policies and behaviours. Dr. Gyimah has published in leading journals such as the *Journal of Corporate Finance*, *British Accounting Review*, *International Review of Financial Analysis*, *Review of Quantitative Finance and Accounting* and the *Journal of International Financial Markets, Institutions and Money*. He also researches sustainable governance, particularly examining how corporate governance influences environmental, social and governance (ESG) practices. For example, his work explores the role of independent board directors in climate change commitments and ESG performance.

Imran Ali is a lecturer (assistant professor) in supply chain management at Queen Mary University of London. His research spans the digitisation of supply chains, innovative operations management and technology and innovation management. He explores the integration of interorganisational and intraorganisational supply chain data, big data analytics and technological innovation within supply chains. Dr. Ali has published extensively across academic journals, books and practitioner outlets. His peer-reviewed articles appear in leading journals such as *Supply Chain Management: An International Journal*, *International Journal of Production Economics*, *International Journal of Production Research*, *Technovation* and *International Business Review*. His work covers machine learning for sustainable agri-food supply chains, blockchain to enhance supply chain trust, AI in manufacturing and the synergy between blockchain and big data analytics in SMEs. He is also co-editor of *Advanced Technologies and the Management of Disruptive Supply Chains: The Post-COVID Era* (Springer Nature), a comprehensive volume addressing resilient supply chain management postpandemic. Additionally, Dr Ali has contributed book chapters on sustainable urban logistics, procurement transparency and digital transformation in manufacturing supply chains. Beyond academia, he disseminates his research via practitioner-focused publications for DHL, Sedex and Future Factory, helping bridge theory and practice.

Christian Gnakepe is an associate professor of strategy, entrepreneurship and Innovation at Toulouse Business School. His research focuses on sustainable innovation, circular economy practices and the strategic acquisition and governance of green technologies across construction, aerospace and biopharma. Dr. Gnakepe is known for employing advanced quantitative methods, including AI-enabled machine learning, to analyse innovation dynamics and energy efficiency outcomes. He has published in several leading journals, including the *Journal of Business Research* and *Technology Forecasting for Social Change*.

Mélanie Roux is an assistant professor in entrepreneurship, innovation management and strategy at Toulouse Business School. She obtained her PhD in Management Sciences from IAE Aix-Marseille in France. Her current research focuses on the sustainable use of artificial intelligence in innovation, sustainable innovation and the value of intrapreneurship in meeting major societal challenges. She has published articles in leading peer-reviewed journals, including the *Journal of Business Research* and the *Review of Entrepreneurship*.

Amelie Abadie is an assistant professor of Marketing at TBS Education Casablanca Campus, Morocco. Her research focuses on digital ecosystems, with a special focus on the influence of artificial intelligence on value co-creation and organisations. In the context of AI and other technologies such as blockchain and deep learning, her research examines strategies and effective policies to enhance AI socialisation and the impact of emerging technologies on achieving sustainable business operations. She is also looking at digital solutions and antecedents to their adoption for developing green conscience among consumers in both developing and developed economies. Her works have appeared in the *Journal of Business Research*, the *Human Resource Management Review*, *l'Economie Politique*, *Colloquium on European Research in Retailing*, *International Conference on System Sciences HICSS* or in book chapters of *Distribution 4.0*.