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Impact of AI strategies on climate-change performance: Responsible AI and crisis management perspectives

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ABSTRACT

Addressing the Sustainable Development Goal related to climate change through artificial intelligence (AI) is an important area of interest for scholars, practitioners, and policymakers. This study examines how AI based strategies, hereafter *AI strategies* – including AI data management and quality, AI analytics, and AI-driven insights employed by the firms – impacting the climate change performance. It emphasizes the mediating role of climate crisis management (risk identification, risk assessment, and crisis response monitoring and treatment) and the moderating role of responsible AI. Using survey data from 235 managers of firms in the USA and Canada, findings reveal that climate risk identification and assessment significantly mediate the positive effects of AI strategies on climate change performance. These indirect effects are stronger under conditions of high responsible AI embeddedness. While crisis response monitoring and treatment also show a positive indirect relationship with climate change performance, this effect does not significantly differ based on the level of responsible AI. The research contributes to crisis management literature by highlighting the critical role of embedding responsible AI strategies for effective climate crisis management, especially in accurately identifying crisis types and assessing their severity. Additionally, we provide a structured 3x3 matrix that offers managerial guidelines drawing insights from data-derived findings and present critical research avenues for future exploration. Practically, these findings assist managers in effectively integrating responsible AI practices into crisis management processes to enhance firms' climate performance and resilience.

1. Introduction

"AI's potential to help mitigate the worsening climate crisis and improve adaptation and resilience is immense. By harnessing AI, we can better predict climate patterns, optimize energy use, and develop more sustainable practices" Christoph Schweizer, CEO of Boston Consulting Group.

Climate change poses escalating risks, with projected climate-related damage costs reaching \$1.7–\$3.1 trillion annually by 2050 (WEF, 2023). Organizations are already experiencing operational disruptions from extreme weather events like wildfires, hurricanes, and floods (Khan et al., 2023), along with rising costs for infrastructure adaptation and resilient systems. Businesses failing to integrate sustainable practices risk financial penalties, market losses, and reputational damage (Isaacs et al., 2023; WEF, 2024b). Accordingly, addressing these risks requires strategic action to enhance resilience across business sectors.

From practitioners' standpoint, businesses have traditionally relied on climate modeling to assess risks and develop sustainability strategies, but these methods often fall short in capturing the complexity of climate change (WEF, 2024a; BCG, 2022). Businesses usually adopt AI-driven predictive analytics, scenario modeling, and risk assessment tools for strategic decision-making. AI-powered machine learning algorithms enhance emissions forecasting, resource optimization, and climate resilience planning (IBM, 2023; Microsoft, 2024), while geospatial analytics and supply chain models help organizations monitor vulnerabilities and adapt operations accordingly (BCG, 2021). However, traditional climate models have significant limitations—they process

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data slowly, rely on static assumptions, and struggle to detect complex climate patterns, limiting their ability to support real-time decision-making (Randall et al., 2007). Many models remain sector-specific, lacking a holistic perspective on climate risks. These shortcomings highlight AI's potential to enhance climate modeling through faster, adaptive, and data-driven insights, making it a more effective tool for businesses navigating climate challenges.

While policy reports on climate change (e.g., IPCC, 2023; UNEP, 2024; UNFCCC, 2023; World Bank Group, 2021) emphasize AI as a key technology for enhancing climate resilience and adaptation, aligning with Sustainable Development Goal 13 (SDG13). In this study, we shift the unit of analysis from isolated AI tools to a comprehensive firm-level AI strategy. Rather than focusing on individual applications, we conceptualize AI strategies as an integrated approach that embeds AI into organizational processes to support climate action (Sullivan and Wamba, 2024; Shankar and Gupta, 2024). This strategy seamlessly integrates AI's capabilities in data management, analytics, and insights generation to tackle climate challenges, empowering firms to enhance their sustainability efforts effectively. That is, an AI strategy extends beyond adopting new technology–it requires integration into core operations to drive business performance and sustainability. At its core, AI enables organizations to efficiently process vast environmental data, apply advanced analytics to identify critical climate patterns, and translate findings into actionable strategies (Kumar et al., 2024b). The foundation of AI's effectiveness lies in high-quality, reliable data, which enhances its ability to predict climate trends and monitor environmental changes (Aldoseri et al., 2023). Analytics processes this data, adapting to changing conditions to generate actionable insights (Cowls et al., 2023; Liu et al., 2022). These AI insights translate analytics into strategic actions, helping businesses align climate goals with operations and improve sustainability performance (Isaacs et al., 2023; Olaniyi et al., 2023).

Marketplace evidence shows that implementing AI strategies have significantly improved both operational efficiency and sustainability, cutting electricity consumption by up to 15 %, reducing emissions by 13 %, and boosting power efficiency by 11 % (Deloitte, 2024; Finio and Downie, 2023; McElhaney et al., 2023; BCG, 2023). Agribusinesses in regions such as California and India are using ClimateAi's AI-powered platform to access high-resolution climate forecasts during droughts. These insights support timely decisions on planting and sourcing, helping protect crop yields while minimizing supply chain disruptions and financial losses (Aziz, 2022). Similarly, businesses in flood-prone areas are leveraging Google's AI-powered flood forecasting system to receive early warnings, enabling them to safeguard assets, reroute deliveries, and maintain operations during extreme weather events (World Bank Group, 2023).

Addressing climate change requires a structured framework that enables organizations to anticipate, assess, and respond to emerging threats. Climate Crisis Management (CCM) provides such a framework, integrating risk identification, risk assessment, and crisis response (monitoring and treatment) to enhance organizational resilience (Farrokhi et al., 2020; Leal Filho et al., 2022; Shankar and Gupta, 2024; Oetzel and Oh, 2021). AI enhances CCM by scanning vast datasets, detecting early warning signs, prioritizing risks, and optimizing real-time crisis response (Caner and Bhatti, 2020; Bibri et al., 2024; Nishant et al., 2020). Rooted in crisis management theory, CCM leverages AI-driven insights and real-time analytics to improve risk anticipation and decision-making (Gupta et al., 2022; Khalilpourazari and Pasandideh, 2021). As climate risks become increasingly complex and unpredictable, a data-driven, proactive approach like CCM is essential for ensuring climate resilience and sustainability (Akter et al., 2024; Bibri et al., 2024). By integrating AI into CCM, this study extends existing crisis management theories by demonstrating how AI can strengthen organizational climate adaptation capabilities and contribute to long-term environmental sustainability (Arora et al., 2024; Leal Filho et al., 2022).

As AI becomes central to climate strategies, its integration must be guided by responsible AI principles (Tutun et al., 2023; Liu et al., 2023). Responsible AI ensures transparency, accountability, and inclusiveness, reducing risks such as bias, inequity, and resource misallocation (Buhmann and Fieseler, 2021; Huang and Rust, 2021). Unchecked AI adoption may exacerbate inequalities or erode trust in climate solutions (Heinrich et al., 2019; Mikalef et al., 2022). Therefore, embedding responsible AI into climate strategies is essential to ensure that AI enhances resilience fairly and ethically (Leal Filho et al., 2022; Sundberg, 2024).

Several gaps remain despite the growing body of research on AI applications in environmental sustainability and climate action. First, while there is extensive literature on the use of AI in environmental monitoring and predictive analytics (Kumar et al., 2024b), there is a lack of comprehensive frameworks that integrate AI strategies into broader corporate CCM (Cowls et al., 2023). The existing studies often focus on isolated applications of AI rather than on holistic, strategic approaches that align AI with organizational goals and climate resilience (Akter et al., 2024; Nishant et al., 2020). Second, the literature on responsible AI, particularly in the context of climate change, is still in its nascent stages. There is a need for a more in-depth exploration of how AI strategies can be designed and implemented in a manner that is ethical, transparent, and inclusive (Kanungo et al., 2024; Liu et al., 2022; Tutun et al., 2023). Finally, while the impact of AI on organizational performance in the context of climate change has been acknowledged, there is limited empirical evidence on how AI-driven strategies can enhance climate change performance, particularly in terms of cost-effectiveness, resilience, and sustainability (Singh and Goyal, 2023). Addressing these gaps is crucial for advancing the integration of AI into climate strategies and ensuring that these technologies contribute positively to organizational sustainability efforts. Therefore, we aim to address two main research questions.

- *How do AI strategies impact Climate Crisis Management and, ultimately, Climate Change Performance?*
- *What role does responsible AI play in the relationship between AI strategies and Climate Crisis Management for Climate Change Performance?*

This study makes four key contributions to the literature on AI strategy, climate crisis management (CCM), and climate change performance. First, it conceptualizes AI strategy as a structured framework that enhances climate change performance by improving risk identification and assessment but reveals limitations in AI-driven crisis response monitoring and treatment (Akter et al., 2021a,b; Kumar et al., 2024b). Second, it advances the understanding of AI's role in CCM, demonstrating that AI significantly improves proactive risk management but does not translate into effective crisis response outcomes, highlighting the need for further refinement in AI-driven emergency interventions (Leal Filho et al., 2022; Xiao and Yu, 2025). Third, it highlights responsible AI's moderating role, showing that ethical and transparent AI strengthens the relationship between AI strategy and risk identification/assessment, but does not enhance AI's role in crisis response, indicating that responsible AI alone may not be sufficient to optimize real-time crisis interventions (Cowls et al., 2023; Mikalef et al., 2022). Finally, this study refines the link between AI strategy and climate change performance, emphasizing that AI's effectiveness depends on how well it integrates into structured risk management processes rather than crisis response mechanisms (Bibri et al., 2024; Huang and Rust, 2024). These findings provide a more nuanced understanding of AI's role in climate action, offering valuable insights for both theory and practice.

The remainder of this paper is organized as follows. Section two presents the theoretical background, drawing from the resource-based view, crisis management theory, and responsible innovation frameworks with the conceptual model and hypotheses. Section three introduces the methodology of the paper. Section four outlines the data collection procedures. Section five presents discussion and conclusion, and the theoretical and practical implications. Section six concludes with limitations and future research directions.

2. Theoretical background, literature review and hypotheses

This study is grounded in multiple theoretical perspectives to explain how artificial intelligence (AI) strategies contribute to climate crisis management (CCM) and climate change performance. Specifically, we draw on the Resource-Based View (RBV), Crisis Management Theory, and the Responsible Innovation Framework to inform our conceptual model and hypothesis development.

The Resource-Based View (RBV) (Barney, 2001) allows us to conceptualize AI strategy as a strategic and valuable resource composed of data infrastructure, analytical capabilities, and AI-generated insights. These capabilities help firms gain a competitive advantage by improving climate-related decision-making. In our model, AI strategies are positioned as firm-level resources that enhance environmental performance by enabling more informed, timely, and data-driven interventions. This perspective aligns with past studies showing that advanced digital technologies, including AI, can strengthen sustainability and operational outcomes (Bibri et al., 2024; Ghaffarian et al., 2023; Akter et al., 2024).

For our mediating framework, we incorporate the climate crisis management framework, which outlines a systematic cycle of risk identification, risk assessment, and risk monitoring and treatment (response). Rooted in crisis management theory, CCM leverages AI-driven insights and real-time analytics to improve risk anticipation and decision-making (Gupta et al., 2022; Khalilpourazari and Pasandideh, 2021). This framework provides a normative model for organizational risk management and is widely used in climate-related planning and reporting (Gupta et al., 2022; Singh and Goyal, 2023). It supports our conceptualization of CCM as a process-based construct and guides the inclusion of mediation pathways in our study.

Finally, we integrate theoretical insights from the responsible innovation framework (Stilgoe et al., 2020) to support the moderating role of responsible AI. This framework emphasizes the importance of ethics, transparency, inclusivity, and reflexivity in the development and deployment of emerging technologies. Given increasing concerns about algorithmic bias, lack of explainability, and ethical risks in AI deployment, we posit that responsible AI practices enhance the impact of AI strategies on climate outcomes. Recent work supports this view, arguing for the necessity of responsible AI in achieving fair, effective, and accountable climate action (Kanungo et al., 2024; Liu et al., 2022; Tutun et al., 2023). Together, these theoretical perspectives offer a multi-dimensional understanding of how and why AI strategies influence climate change performance, addressing both capability development and ethical governance in the context of climate crisis management. In the next section we present the literature review.

2.1. AI strategy for climate action

AI strategy provides a blueprint for integrating AI into an organization, enabling it to advance and innovate business processes in alignment with its overarching business and digital ambitions (Huang and Rust, 2021; Kumar et al., 2024b). AI strategies help translate corporate objectives into a clear vision where AI not only makes current operations more efficient but also encourages new, creative ways of doing business (Gama and Magistretti, 2025). It does so by empowering organizations to gain deeper insights from data, enhance employee and customer experiences, boost productivity, and build a stronger supply chain or ecosystem (Broekhuizen et al., 2023; Huang and Rust, 2024; Johnson et al., 2022). For example, AI algorithms can monitor iceberg changes up to 10,000 times faster than traditional methods like manual data collection and analysis, which will greatly improve organizations' ability to predict meltwater release and assess its impact on sea level rise (Masterson, 2024). Similarly, researchers at the University of Leeds have developed advanced AI technology capable of mapping large Antarctic icebergs in satellite images in just one-hundredth of a second (Lucy, 2023). This AI innovation will allow organizations to monitor these critical environmental changes with unparalleled accuracy and speed, capabilities that were previously unattainable with traditional methods.

Businesses must recognize climate change as a strategic priority (Leal Filho et al., 2022; Singh and Goyal, 2023). While many studies have explored the integration of AI to improve environmental monitoring and performance, they often use AI as a tool for driving outcomes or making decisions (e.g., Yuan et al., 2020; Hino et al., 2018). Alternatively, this research proposes a more structured and comprehensive AI strategy for climate action. By leveraging AI as a strategic tool, organizations can better respond to emerging climate challenges. From a strategic perspective, firms are increasingly leveraging AI as a strategic tool for data generation, general-purpose machine learning, and domain-specific insights (Arora et al., 2024; Ratten et al., 2024; Huntingford et al., 2019). These applications reflect a growing organizational commitment to embedding AI as a core driver for informed decision-making (Tutun et al., 2023). Building on this foundation, and in line with past research, we conceptualize an AI-based strategy for climate action as the systematic integration and application of AI technologies to collect, analyze, and interpret environmental data (Akter et al., 2021a,b; Shankar and Gupta, 2024).

First, data serves as the foundation of AI strategies, driving the development, deployment, and continuous enhancement of robust AI models (Akter et al., 2021a,b; Leal Filho et al., 2022). The success of an AI climate strategy relies on identifying relevant data and managing its quality (Caner and Bhatti, 2020; Singh and Goyal, 2023), as flawed data can lead to poor climate change decisions (Akter et al., 2021a,b; Shankar and Gupta, 2024). Reliable and valid data enhances the credibility of environmental assessments and forecasts, fostering trust and collaboration among stakeholders, including governments, organizations, and the public (Gupta et al., 2022; Singh and Goyal, 2023). For example, in the case of weather forecasting, inaccurate data led to significant strategic errors, such as those observed during Hurricane Sandy (Magnusson et al., 2013). Second, AI analytics play a crucial role in developing and implementing a comprehensive AI strategy, as large datasets are analyzed to uncover complex environmental patterns and trends (Shankar and Gupta, 2024; Nahar, 2024).

These insights are then translated into clear, understandable reports, which help stakeholders make informed climate action decisions (Dwivedi and Wang, 2022; Gupta et al., 2022). For example, Nguyen et al. (2021) show improvements in accuracy in company emissions predictions by up to 30 % when high-performance AI algorithms are implemented.

Finally, actionable insights drawn from the processed data and analytic models help decision-makers make informed and proactive climate-competent decisions (Ghaffarian et al., 2024). AI analytics offer a deeper understanding of the trends, but this understanding is to be complemented by industry information, benchmarks, and established frameworks (Dwivedi and Wang, 2022; Nishant et al., 2020). Aligning AI climate insights with organizational goals ensures that these insights enhance the organization's strategic decision-making capabilities related to climate competence (Al-Surmi et al., 2022; Leal Filho et al., 2022). For example, Microsoft's AI strategy includes collaboration with various stakeholders to address environmental challenges, improving the models' local impact (Choney, 2018).

2.2. AI strategies and climate change performance

Climate change performance has been conceptualized in various ways depending on the context, whether at the corporate, institutional, or national level, with prior research identifying several key dimensions including greenhouse gas emissions, renewable energy use, energy efficiency, climate governance, and resilience (Akter et al., 2024; Leal Filho et al., 2022; Wang et al., 2020). This multidimensionality reflects the complex and evolving nature of climate-related challenges (George et al., 2021; Herandez et al., 2021). For businesses in particular, their performance on climate related issues reflects how committed and capable they are in dealing with environmental risks while staying competitive (Khan et al., 2023). Given the context of our study and in line with past research, we define climate change performance as the extent to which a firm's AI strategy contributes to: (1) reducing greenhouse gas emissions, indicating the firm's role in climate mitigation; (2) enhancing resilience and adaptation, reflecting its ability to respond to and recover from climate-related disruptions; and (3) achieving cost-effectiveness, demonstrating efficient use of resources in addressing climate challenges.

AI strategies play a pivotal role in enhancing climate change performance by integrating advanced data analytics, predictive modeling, and real-time decision-making into organizational sustainability efforts (Bibri et al., 2024). AI-powered systems collect and analyze vast amounts of environmental data, offering deeper insights into emission patterns, resource utilization, and areas for optimization (Chavhan et al., 2022). These insights enable organizations to adopt proactive measures that improve efficiency, reduce emissions, and enhance sustainability.

Research has shown that firms leveraging machine learning algorithms and neural networks can improve energy demand forecasting and carbon footprint reduction, enabling them to implement more effective climate mitigation strategies (Huntingford et al., 2019). AI-powered geospatial analytics and climate modeling further support climate adaptation efforts, helping businesses identify emerging environmental risks and integrate sustainability practices into their long-term strategies (Chen et al., 2023a; Khalilpourazari and Pasandideh, 2021). By enhancing climate risk assessment and scenario planning, AI strengthens organizational resilience and adaptability to climate disruptions.

AI-driven simulations allow companies to model the impact of extreme weather events on their operations and supply chains, providing predictive insights that guide contingency planning and disaster preparedness (Bibri et al., 2024; Khalilpourazari and Pasandideh, 2021). These proactive strategies help organizations mitigate the financial and operational risks associated with climate-related disruptions, minimizing costly recovery efforts and ensuring business continuity (Ghadge et al., 2020). Furthermore, AI-powered decision support systems integrate regulatory compliance frameworks, aiding firms in aligning their operations with evolving environmental policies (Nguyen et al., 2021; Ghaffarian et al., 2023).

However, despite these promising outcomes, the effectiveness of AI strategies is not guaranteed. Several contingencies such as limited technical capacity, poor data infrastructure, algorithmic opacity, and organizational resistance can inhibit the successful deployment of AI for climate action (Mikalef et al., 2022; Buhmann and Fieseler, 2021). In some cases, poorly implemented AI initiatives may even result in resource misallocation, unintended biases, or regulatory non-compliance, ultimately undermining climate performance goals (Heinrich et al., 2019). Therefore, while AI holds considerable potential, its impact on climate performance remains conditional and warrants empirical validation.

H1. AI strategies explicitly designed for climate crisis management will positively influence climate-change performance.

2.3. AI strategies and climate crisis management

Climate Crisis Management (CCM) is essential for helping organizations anticipate, assess, and mitigate risks associated with climate change, including extreme weather events, resource scarcity, and regulatory challenges (Farrokhi et al., 2020; Leal Filho et al., 2022). Crisis management is traditionally defined as the systematic monitoring and assessment of threats, leading to the formulation of strategies for risk mitigation (Aljuhmani and Emeagwali, 2017; Shankar and Gupta, 2024). In the context of climate change, AI-driven crisis management offers significant advantages by providing real-time risk identification, predictive analytics, and automated response mechanisms. AI enhances decision-making capabilities by improving opinion formation, consensus-building, and public participation, ensuring that organizations can develop more adaptive and data-driven climate strategies (Coeckelbergh and Sætra, 2023). Traditional crisis management approaches, which rely heavily on historical data and static analysis, often fail to keep pace with rapidly evolving climate threats (Farrokhi et al., 2020; Xiao and Yu, 2025). AI bridges this gap by augmenting human decision-making with advanced computational tools, improving both crisis anticipation and response effectiveness (Shankar and Gupta, 2024).

AI-based technologies are increasingly employed to predict, analyze, and respond to climate-related threats across diverse sectors. These applications include extreme weather forecasting (Gupta et al., 2022), monitoring water scarcity (Katimbo et al., 2023), environmental impact assessments (Akter et al., 2024; Hino et al., 2018), and biodiversity conservation (Abdollahi and Pradhan, 2021). AI also plays a role in marine conservation efforts, sustainable urban planning, and illegal wildlife trade monitoring, demonstrating its broad applicability in climate crisis management (Elam, 2023; Girard and Du Payrat, 2017). Many of these initiatives rely on AI-driven intelligent systems, such as smart energy grids, electric vehicles, and climate-resilient manufacturing processes, which optimize energy efficiency and environmental sustainability (Cowls et al., 2023; Ghaffarian et al., 2023; Atitallah et al., 2020).

One of the most significant challenges in climate crisis management is analyzing large, complex datasets and generating actionable insights. Traditional risk assessment models, while valuable, often rely on static datasets and retrospective analysis, limiting their ability to predict emerging climate threats (Chen et al., 2023b). These models struggle with adapting to new data in real time, reducing their effectiveness in dynamic, rapidly changing environments (Labe and Barnes, 2021; Xiao and Yu, 2025). AI overcomes these limitations by utilizing machine learning algorithms and real-time data analytics to continuously refine climate risk assessments (Leal Filho et al., 2022; Singh and Goyal, 2023).

AI strategies provide organizations with early warning capabilities by continuously monitoring climate variables and anomalies, allowing for timely risk mitigation efforts (Bibri et al., 2024). By integrating satellite imagery, IoT sensors, and historical climate data, AI-powered systems can detect emerging patterns and forecast potential disasters with greater accuracy (Nahar, 2024; Khalilpourazari and Pasandideh, 2021). For example, Jones et al. (2023) demonstrated how AI-driven flood risk models significantly improved disaster preparedness by integrating satellite observations, weather forecasts, and historical flood records. Early detection allows organizations to adjust their strategies, reinforce infrastructure, and allocate resources effectively, reducing vulnerabilities before crises escalate. Given AI's ability to enhance climate crisis management through early risk detection and predictive modeling, we propose.

H2a. The implementation of AI strategies explicitly designed for climate crisis management will positively influence an organization's ability to identify climate risks.

AI strategies significantly enhance crisis risk assessment by leveraging predictive modeling and real-time analytics, enabling organizations to quantify and evaluate potential climate threats more effectively (Bibri et al., 2024; Chen et al., 2023a). AI-driven models assess the likelihood, severity, and potential impact of extreme events such as heatwaves, droughts, and hurricanes, allowing firms to make informed decisions on risk prioritization and resource allocation (Huntingford et al., 2019; Kankanamge et al., 2021). Unlike traditional risk assessment methods, which often rely on historical data and static models, AI-powered risk assessments dynamically adapt to changing climate conditions, improving accuracy and decision-making agility

(Gupta et al., 2022; Nahar, 2024).

In crisis situations, AI can evaluate an organization's level of exposure by analyzing real-time environmental data, helping firms prepare for disruptive climate events and implement proactive mitigation strategies (Akter et al., 2024; Sankaranarayanan et al., 2020). AI-powered systems provide predictive timelines, allowing businesses to anticipate risks and make preemptive adjustments to their operations, supply chains, and infrastructure before crises escalate. By integrating machine learning algorithms and scenario modeling, AI enhances firms' ability to simulate various climate risk scenarios, strengthening their strategies for adaptation and preparedness (Ghaffarian et al., 2023; Kankanamge et al., 2021).

AI-based risk assessments also enable organizations to prioritize threats based on their potential operational and environmental impact, ensuring that resources are allocated efficiently to high-risk areas (Dwivedi and Wang, 2022). This strategic approach improves crisis resilience, minimizes financial losses, and optimizes emergency response planning. By automating risk evaluation processes, AI empowers firms to develop and refine intervention strategies that mitigate climate-related disruptions effectively. Given AI's capacity to enhance climate risk assessment through predictive modeling and data-driven insights, we propose.

H2b. The implementation of AI strategies explicitly designed for climate crisis management will positively influence an organization's ability to assess climate risks.

When there is a crisis, AI-driven systems play a critical role in enhancing emergency response management by providing real-time insights, automating decision-making, and optimizing resource deployment (Gupta et al., 2022; Singh and Goyal, 2023). AI enables crisis containment and recovery by continuously analyzing data from drones, satellites, IoT sensors, and ground monitoring systems, allowing organizations to track crisis progression and adjust response strategies dynamically (Akter et al., 2024; Damoah et al., 2021). Unlike traditional crisis management approaches, which often rely on delayed or incomplete information, AI systems process incoming data streams in real time, facilitating faster and more precise interventions (Singh and Goyal, 2023; Gama and Magistretti, 2025).

AI enhances logistics coordination and resource optimization by enabling firms to prioritize emergency response efforts based on the severity and location of disruptions (Chen et al., 2023a; Leal Filho et al., 2022). AI-driven models simulate various crisis response scenarios, allowing decision-makers to anticipate challenges, test different intervention strategies, and deploy the most effective response plans (Karinshak, 2024; Khalilpourazari and Pasandideh, 2021). These simulations are particularly valuable in predicting secondary impacts, such as aftershocks following earthquakes or post-hurricane flooding, enabling responders to take preemptive action to mitigate further risks (Sahoo and Bhaskaran, 2019).

Furthermore, AI-powered disaster mapping and damage assessment tools improve response efficiency by identifying high-risk zones and critical infrastructure failures. For instance, the xView2 project, a collaboration between Microsoft and the University of California, Berkeley, employs AI to map disaster-affected areas in real time, assess the extent of damage, and determine safe locations for emergency shelters, thereby aiding both immediate relief efforts and long-term recovery planning (Ryan-Mosley, 2023). These AI-driven solutions significantly enhance situational awareness, ensuring that crisis managers can make informed, data-driven decisions that maximize response effectiveness.

By leveraging AI for real-time crisis monitoring and adaptive response strategies, organizations can improve disaster preparedness, reduce economic losses, and enhance climate resilience. Therefore, we hypothesize.

H2c. *The implementation of AI strategies explicitly designed for climate crisis management will positively influence an organization's ability to monitor and treat climate risks.*

2.4. Mediating role of climate crisis management

Climate crisis management ensures that identified risks are not only recognized but also effectively managed through a structured process of assessment, response, and treatment, leading to significant improvements in climate-change performance (Bibri et al., 2024; Yuan et al., 2017). Effective risk identification is crucial for CCM as it directly influences climate-change outcomes. When risks are correctly identified, it allows for targeted and timely interventions. Employing AI-driven strategies enables organizations to prioritize actions that address the most significant threats, build resilience by identifying vulnerabilities, and develop adaptive measures for climate-related events (Ye et al., 2021; Shankar and Gupta, 2024). These strategies help organizations identify and prioritize risks and focus on urgent threats, leading to more effective interventions and better resource allocation (Ciulli and Kolk, 2023). Targeted crisis assessments not only help reduce costs by directing resources effectively but also emphasize interventions with the highest return on investment (Gama and Magistretti, 2025). Similarly, effective monitoring allows for fast adaptation to changing circumstances, which is essential in managing the unpredictable nature of climate crises (Nishant et al., 2020; Sankaranarayanan et al., 2020). This flexibility ensures that responses remain effective as conditions shift, ultimately saving resources and reducing waste.

H3a-c: *(a) Risk identification, (b) risk assessment, and (c) crisis response monitoring and treatment will mediate the relationship between AI strategies explicitly designed for climate crisis management and climate change performance.*

2.5. Moderating role of responsible AI

AI strategies can fail due to factors like insufficient, outdated, or biased data, as well as their potential to produce recommendations and decisions that lead to unforeseen and adverse outcomes (Buhmann and Fieseler, 2021; Heinrich et al., 2019). For example, if training datasets reflect historical inequalities or skewed perspectives, the strategies suggested by the AI models may unintentionally reinforce these biases (Kumar et al., 2024b; Ooi et al., 2023). Similarly, the lack of transparency in AI decision-making can undermine trust and accountability (Bibri et al., 2024; Shankar and Gupta, 2024), leading to resistance from communities and policymakers and hindering the effective implementation of AI-driven climate solutions (Bibri et al., 2024). Finally, the development and deployment of AI technologies, such as the production of AI hardware, involves the extraction of rare earth metals, while the operation of large-scale models demands substantial computational power (Bibri et al., 2024; Van Wynsberghe, 2021). If not managed responsibly, these processes can contribute to carbon emissions, leading to harmful environmental consequences.

Due to these shortcomings, practitioners and researchers emphasize the need for responsible AI that prioritizes ethical standards, transparency, and accountability (Kanungo et al., 2024; Voegtlin and Scherer, 2017). The term Responsible AI is often used synonymously with ethical AI or the application of AI in a responsible manner (Liu et al., 2023). According to Eitel-Porter (2021), responsible AI refers to the intentional and ethical use of AI to empower employees and businesses while fostering fairness for customers and society, ultimately helping organizations build trust and effectively scale their AI initiatives. It allows organizations to enhance societal well-being by integrating responsible principles and ethical decision-making that align with societal, ethical, and legal standards while protecting privacy, mitigating biases, ensuring transparency, providing reliable insights, and promoting fairness, particularly in crisis management (Kanungo et al., 2024; Mikalef et al., 2022).

When a firm is committed to using AI systems ethically and responsibly, it can enhance the integrity of AI based strategies for sustainable actions (e.g., climate change). Furthermore, it ensures transparency in data handling and avoid biases in assessments (ibid), that may enhance the efficacy of sustainability related actions such as climate crisis management for climate performance. Given responsible AI encourages fair and inclusive decisions, clear and transparent information sharing with stakeholders, and promotes governance to ensure that strategies and related decision making are ethical and free from bias (c.f. Kanungo et al., 2024; Kumar et al., 2023; Kumar et al., 2024b; Mikalef et al., 2022). Hence, one can argue that by doing so, it enhances the firm's AI strategies for sustainability actions with integration of responsibility and governance.

Responsible AI should address the challenge of balancing the benefits of AI with mitigating its potential harms while also preventing both the misuse and underuse of AI technologies (Liu et al., 2023). Researchers and business organizations have introduced a range of principles, approaches, and practices for responsible AI, enriching the diverse categorizations and frameworks that are now prominent in the current AI literature and practice (e.g., Arrieta et al., 2020; Benjamins et al., 2019; Ghallab, 2019; Liu et al., 2023; Lyons et al., 2021). For example, Arrieta et al. (2020) suggested that AI models should prioritize fairness, ethics, transparency, security and safety, accountability, and privacy. Implementing these principles in real-world applications could lead to a gradual increase in corporate awareness regarding responsible AI practices. Similarly, Microsoft has established the Office of Responsible AI (ORA) and the AI, Ethics, and Effects in Engineering and Research (Aether) Committee to implement and operationalize responsible AI principles in their practices (Microsoft, 2020).

Companies pursuing responsible AI establish a clear ethical framework that guides AI activities, focusing on minimizing biases and using diverse, high-quality data (Kumar et al., 2024b; Raji, 2024). In CCM, where identifying potential risks is crucial, responsible AI enhances the reliability of risk assessments by reducing algorithmic bias, ensuring ethical decision-making, and promoting transparency (Cowls et al., 2023; Tutun et al., 2023). As AI technology improves in reliability and safety, users are more likely to trust and adopt AI tools for crisis management (Akter et al., 2024; Eitel-Porter, 2021). By recognizing the benefits and effectiveness of AI strategies, users are more engaged and willing to use these tools to identify, assess, and monitor crises (Liu et al., 2023).

By addressing biases through diverse datasets, responsible AI leads to more accurate and equitable climate risk assessments, particularly for vulnerable regions, and builds trust through transparency and accountability, resulting in better outcomes for affected communities (Trocin et al., 2023; Cowls et al., 2023). Through its robust algorithms and enhanced analytical capabilities built on ethical frameworks, responsible AI systems can provide effective solutions by accurately identifying challenges, minimizing biases, and ensuring that decisions are both fair and transparent (Huang and Rust, 2024; Mikalef et al., 2022). This ethical foundation ensures that AI-driven interventions are not only efficient but also align with societal values, leading to more equitable and impactful crisis management solutions (Abulibdeh et al., 2024; Cowls et al., 2023).

H4a-c. The positive indirect effect of AI strategies explicitly designed for climate crisis management on climate change performance through (a) risk identification, (b) risk assessment, and (c) crisis response monitoring and treatment is significantly stronger at higher levels of responsible AI compared to lower levels.

Addressing the climate change crisis requires more than just adjusting existing strategies; it calls for a comprehensive transformation of the company's strategic infrastructure to mitigate climate impacts and ensure long-term sustainability (Akter et al., 2024; Bibri et al., 2024; Leal Filho et al., 2022). Accordingly, companies must tackle the significant challenge of decarbonizing their operations, enhancing their resilience and adaptability, and reducing operational costs. To address these challenges effectively, this research explores how an AI strategy, including aspects such as AI data quality and availability, advanced AI analytics, and actionable AI insights, can significantly improve CCM. Additionally, this research examines the mediating role of CCM by investigating how effectively identifying, assessing, and responding to climate risks can enhance climate change performance. Finally, it examines how integrating responsible AI practices can influence the effectiveness of AI strategies in managing climate crises. Based on this discussion, the overall research model is presented in Fig. 1.

3. Research methodology

3.1. Data collection

To evaluate our research hypotheses, we conducted a survey targeting managers employed in companies that have implemented AI for climate change-related initiatives within their business operations. Managers are considered good sources for reliable source of AI based strategy related information given their knowledge and experience in strategic decision making. The data was gathered via an online questionnaire administered through the Prolific crowdsourcing platform.[1] The service ensured accurate participant profiles, allowing us to select a sample that closely matched the desired characteristics for our research (Palan and Schitter, 2018; Peer et al., 2017). We followed the most recent methodological guidelines for Prolific (Palan and Schitter, 2018; Porter et al., 2019) and combined them with advanced survey features and filtering options in Qualtrics, resulting in a significant improvement in data quality.

First, we implemented multiple screening criteria. Respondents were asked to answer three screening questions: (1) Is your organization using AI tools for sustainability and climate action initiatives; (2) How would you rate your proficiency in using AI tools in your managerial role (1 = Not at all proficient, 7 = Expert); and (3) Are you using AI tools for climate action decisions or, at least, know how your organization employs AI tools for such decisions. Only participants who answered yes to questions 1 and 3 and rated their proficiency in using AI tools as at least beginner were allowed to proceed.

We restricted the participation to individuals from English-speaking countries (i.e., the United States and Canada). While these nations are often seen as leaders in environmental protection initiatives, they do not rank among the top 25 countries on the Environmental Performance Index (EPI) (Wolf et al., 2022). As major global players, the environmental strategies and performance of Canada and the US have significant implications for international climate policies and agreements. Moreover, these countries are at the forefront of integrating AI for climate action (U.S. Department of Energy, 2024; Vector Institute, 2024). Hence, studying these countries can provide valuable insights into the global impact of AI strategies on climate action.

High-ranking EPI nations demonstrate strong commitments to biodiversity conservation, environmental health, climate change mitigation, and reducing greenhouse gas emissions through sustained investments. The EPI aggregates data on various sustainability factors into a single score for each country, transforming raw environmental data into indicators that rank nations on a scale from 1, representing the highest performance, to 100, representing the lowest. More importantly, organizations in these countries are actively adopting AI technologies to advance environmental strategies and sustainability efforts (Statista, 2024).

To reduce mono-method bias and enhance both honesty and attention, we employed multiple strategies recommended by previous research (e.g., Goodman et al., 2013; Landers and Behrend, 2015; Palan and Schitter, 2018): (1) we randomized the order of survey questions; (2) we randomly included attention-check questions to verify participants' engagement; (3) we requested participants to agree to provide

[1] Peer et al. (2017, 2021) compared data quality across various crowdsourcing platforms for behavioral research, finding that Prolific ranked highest in response quality and sample diversity.

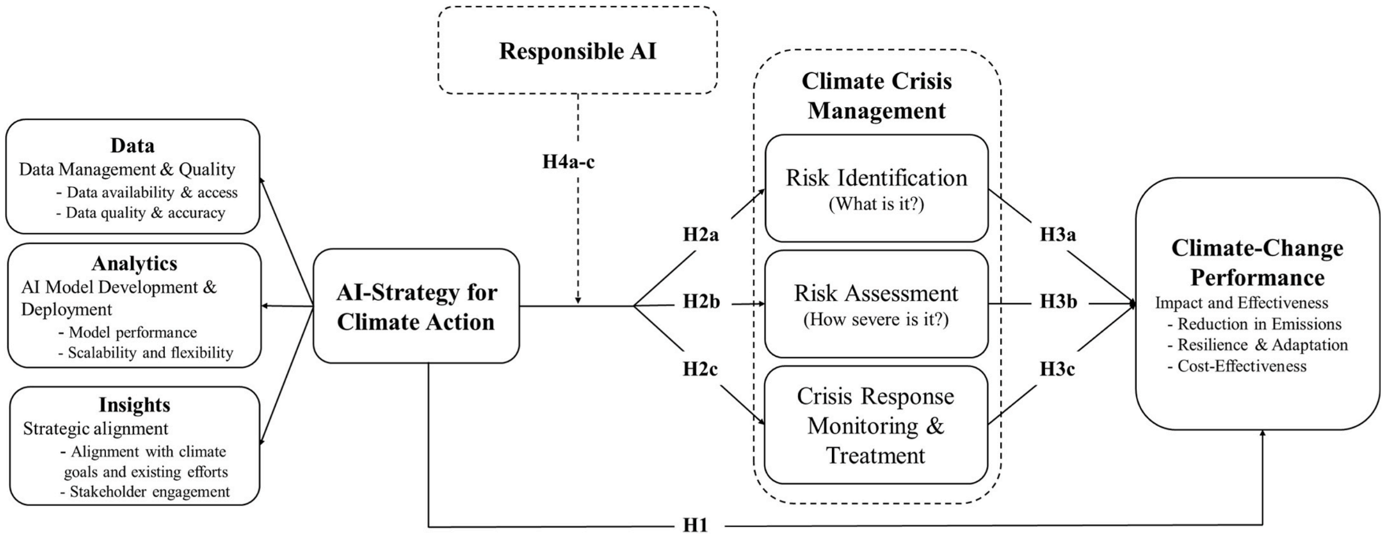

Fig. 1. Research model.

honest and accurate responses; (4) we emphasized to the participants that there are no right or wrong answers to the questions; (5) we highlighted the need for careful attention and the significance of the research study; and (6) we monitored completion times. Similarly, a common issue with self-reports is social desirability bias, which we tried to mitigate using the following measures: First, we used Prolific, a third-party online panel where respondents had no direct interaction with researchers, and researchers had no access to respondents' personal information. Second, we assured participants that their responses would remain anonymous and confidential. These are the leading practices for minimizing social desirability bias (Awad and Ragowsky, 2008; Lowry et al., 2013).

To make sure that the survey instrument is clear and valid, we presented a preliminary version of the survey to a panel of four social science researchers. After incorporating the feedback and suggestions from the panel of members, we recruited 235 respondents from Prolific who met the screening criteria. Of these, 23 were excluded due to (1) failing two or more attention checks, (2) completing the survey significantly faster than the median time, or (3) providing incomplete responses.

Lastly, managers completing the survey were asked to reflect on how the integration of AI, compared to traditional tools used in past or current climate crisis management, has influenced outcomes. They were specifically prompted to assess the impact of AI strategies relative to these conventional methods. This approach was designed to encourage managers to provide a thoughtful and informed comparison between AI-driven solutions and the status quo, thereby offering a deeper understanding of AI's potential in addressing climate challenges. Table 1 presents the sample characteristics in terms of organization age, organization size, operational market, and industry type.

Table 1
Sample profile.

Firm characteristics	Frequency	Percentage
1. Organization age		
less than 5 years	12	5.70 %
5–10 years	45	21.20 %
11–15 years	26	12.30 %
above 15 years	129	60.80 %
Total	212	100 %
2. Organization size		
less than 100	46	21.70 %
101–500	53	25 %
501–1000	56	26.40 %
1001–5000	36	17 %
above 5000	21	9.90 %
Total	212	100 %
3. Operational market		
B2C	119	56.1
B2B	93	43.9
Total	212	100 %
4. Industry type		
Service	115	54.20 %
Manufacturing	97	45.80 %
Total	212	100 %

3.2. Measures

The measures for the constructs were derived from previous research with established scale reliabilities, using a seven-point Likert scale (1 = "strongly disagree," and 7 = "strongly agree"). The list of items comprising each construct is provided in the Appendix. We conceptualized AI strategy for climate action as a second-order reflective construct composed of three first-order reflective dimensions: AI data management and quality, AI analytics, and AI-driven insights. AI data management and quality were measured on a three-item scale, adapted from the cited studies (Akter et al., 2024; Mikalef et al., 2020); these items concerned data availability and quality. AI analytics was measured using a three-item scale adapted from the cited studies (Akter et al., 2024; Sullivan and Wamba, 2024); these items relate to model performance, stability, and flexibility. AI-driven insights were measured on a four-item scale adapted from (Akter et al., 2024; Sullivan and Wamba, 2024); these items focused on the strategic alignment of climate goals with existing efforts and stakeholder engagement. By conceptualizing AI strategy as a second-order reflective construct, we captured the comprehensive nature of AI's impact on climate action. This approach ensures that all critical aspects—data management, analytics, and insights—are considered together, giving us a more complete understanding of AI's role in tackling climate challenges.

Climate risk identification, climate risk assessment, and crisis response monitoring and treatment were each measured using three-item scales adapted from cited studies (Basile et al., 202; El-Baz and Ruel, 2021). Responsible AI was measured using a four-item scale adapted from Kumar et al. (2023) .[2] In line with past research, climate-change performance was conceptualized as a second-order reflective construct composed of three first-order reflective dimensions: reduction in emission, resilience and adaptation, and cost-effectiveness. Each of these dimensions was measured using two-item scales adapted from the cited studies (Akter et al., 2021a,b, 2024; Kumar et al., 2024a).

Based on past research, we also included four control variables that may have a confounding effect on the use of AI strategies on climate change performance: (1) organization size (i.e., number of employees), (2) organization age, (3) operational market (B2C or B2B), and (4) industry type (manufacturing or service).

4. Data analysis

We used covariance based structural equation modelling (CB-SEM) to test our hypotheses. We tested the model using the maximum likelihood (ML) estimation method, as it offers more reliable overall fit indices and yields less biased parameter estimates for overlapping paths within the model compared to alternatives like generalized least squares and weighted least squares (White, 1982). We used CB-SEM with ML estimation because the method is considered suitable for testing hypotheses based on existing theory, which is the case with our study. By allowing for strict model fit evaluation, CB-SEM offers more reliable overall fit indices and yields less biased parameter estimates for overlapping paths within the model compared to alternatives like generalized least squares or partial least squares (PLS) SEM squares (Boomsma, 1987; White, 1982). Additionally, like PLS-SEM, CB-SEM can also be used with higher-order constructs (Al Issa and Abdelsalam, 2021), with comparative studies showing that CB-SEM and PLS-SEM producing similar results (Al Issa and Abdelsalam, 2021; Astrachan et al., 2014).

4.1. Common method bias (CMB)

CMB is a major source of systematic error that distorts the empirical results and the validity of the findings, often leading to inflated correlations between the constructs within a model. Hence, we implemented three procedural remedies. First, we assessed the potential for method variance using Harman's one-factor test. The results reveal that the first factor only accounted for 34.05 % of the variance in the sample. Second, we observed the correlation matrix. A correlation above 0.90 indicates that CMB exists (Pavlou et al., 2007). The correlations between the focal constructs in Table 3, ranging from 0.09 to 0.71, are significantly below the 0.90 threshold. The presence of low correlations among certain constructs also indicates that no single factor influenced all the constructs. Third, we examined the correlation between the key constructs and a marker variable—a theoretically unrelated construct (Lindell and Whitney, 2001). We used life satisfaction as the marker variable in this study. The analysis revealed that the correlation between the marker variable and the focal constructs in our sample was extremely low (−0.05 to 0.04).

4.2. Measurement model

We assessed the factor structure of our measured variables using AMOS 27. Our results in Tables 2 and 3 indicate that the measurement model fit the data well: $\chi2/df = 1.74$, CFI = 0.94; TLI = 0.93; RMSEA = 0.06; SRMR = 0.06. Table 2 shows that most indicator loadings exceeded the 0.70 threshold (Chin, 1998), confirming reliability. All the alpha and CR scores were above 0.70 (Chin, 1998), and AVE scores exceeded 0.50 (Fornell and Larcker, 1981). Table 3 indicates that the square roots of the AVE for each construct exceeded all of the correlations between that construct and the other constructs. HTMT values were also all below the strict standard of 0.85, confirming discriminant validity (Henseler et al., 2015).

4.3. Structural model

Direct effects. We first estimated a direct effect model using AMOS 27. The results showed a good fit between the model and the data: $\chi2/df = 1.65$, CFI = 0.96; TLI = 0.91; RMSEA = 0.06; SRMR = 0.05. Our results, as presented in Fig. 2 and Table 4 reveal that AI strategy has a significant positive impact on climate change performance ($\beta = 0.42$, $p < 0.01$), risk identification ($\beta = 0.47$, $p < 0.01$), risk assessment ($\beta = 0.46$, $p < 0.01$), and crisis response monitoring and treatment ($\beta = 0.50$, $p < 0.01$), supporting H1 and H2a-c. Although we did not hypothesize this outcome, our results indicate that both risk identification ($\beta = 0.17$, $p < 0.05$) and risk assessment ($\beta = 0.21$, $p < 0.05$) had a significant positive impact on climate change performance. However, crisis response monitoring and treatment did not show a significant effect ($\beta = 0.11$, $p = 0.20$).

Mediating effects. We tested the mediation effects using the AMOS plugin (Gaskin and Lim, 2018) and applied a bootstrapping method with 5000 resamples and 95 % bias-corrected confidence intervals (Preacher and Hayes, 2008). Our results reveal that risk identification ($\beta = 0.08$; 95 % CI [0.01 to 0.12]) and risk assessment ($\beta = 0.10$; 95 % CI [0.02 to 0.15]) mediate the relationship between AI strategy and climate change performance, providing support for H3a and H3b. However, crisis response monitoring and treatment didn't mediate this relationship ($\beta = 0.05$; 95 % CI [−0.02 to 0.12]). Hence, H3c was not supported.

Moderating effects. Further, our results in Table 4 show that responsible AI positively moderates the relationship between AI strategy and both risk identification ($\beta = 0.17$, $p < 0.01$) and risk assessment ($\beta = 0.15$, $p < 0.01$). However, responsible AI didn't moderate the relationship between AI strategy and crisis response monitoring and treatment ($\beta = 0.08$, $p = 0.18$). In Fig. 3a–c, we plot the interaction effects.

4.4. Moderated mediation analysis

To test hypotheses H4a-c, we employed the index of moderated mediation test as outlined by Hayes (2015). We utilized the PROCESS macro in SPSS, applying Model 7 with 5000 bootstrap resamples. Results in Table 5 indicate that the positive indirect effects of AI strategy on climate change performance through crisis identification and crisis assessment are stronger at higher levels of responsible AI (crisis identification: $b = 0.15$, $p < 0.01$; crisis assessment: $b = 0.13$, $p < 0.05$) than when at lower levels (crisis identification: $b = 0.06$, $p < 0.01$; crisis assessment: $b = 0.05$, $p < 0.05$), with a significant difference between the two levels (crisis identification: $b = 0.03$, $p < 0.01$; crisis assessment: $b = 0.02$, $p < 0.05$). These results support H4a and H4b. The positive indirect effect of AI strategy on climate change performance through crisis response monitoring and treatment is more positive at a higher level of responsible AI ($b = 0.13$, $p < 0.01$) compared to the lower level ($b = 0.09$, $p < 0.01$); however, the difference between the two levels is not significant ($b = 0.01$, $p > 0.10$). Hence, H4c is not supported.

[2] Kumar et al. (2023) used a formative model to comprehensively capture different aspects of responsible AI for healthcare applications. They aimed to identify and aggregate diverse dimensions of responsible AI relevant to clinical and operational decision-making. In contrast, our study focuses on understanding how a firm's overall commitment to responsible AI influences the relationship between AI strategy and climate crisis management. We conceptualized responsible AI not as a set of distinct practices, but as a general mindset that reflects how ethically a firm approaches the use of AI. Accordingly, we measured responsible AI using four reflective items that align with our conceptual definition and are theoretically appropriate for our research context.

Table 2
Reliability and construct validity.

Indicators	Items	Item loading	Average variance explained	Composite reliability	Cronbach's alpha
AI data management and quality	**3**	0.85–0.92	0.70	0.87	0.87
AI analytics	**3**	0.78–0.83	0.66	0.85	0.85
AI-driven insights	**4**	0.75–0.86	0.64	0.88	0.88
Climate crisis identification	**3**	0.69–0.89	0.69	0.87	0.86
Climate crisis assessment	**3**	0.82–0.92	0.78	0.91	0.91
Climate crisis response	**3**	0.81–0.90	0.70	0.88	0.88
Responsible AI	**4**	0.89–0.94	0.84	0.95	0.95
Reduction in emission	**2**	0.74–0.88	0.67	0.80	0.78
Resilience and adaptation	**2**	0.70–0.72	0.55	0.71	0.71
Cost-effectiveness	**2**	0.81–0.84	0.68	0.81	0.81
Second-order constructs					
AI strategy	**3**	0.76–0.80	0.62	0.83	0.78
Climate change performance	**3**	0.71–0.80	0.57	0.80	0.76

Table 3
Discriminant validity, and correlations.

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1. AI strategy	**0.79**	0.56	0.59	0.63	0.07	0.65	—	—	—	—
2. Crisis identification	0.63**	**0.83**	0.57	0.53	0.08	0.50	—	—	—	—
3. Climate crisis assessment	0.60**	0.55**	**0.88**	0.61	0.13	0.51	—	—	—	—
4. Climate crisis response	0.67**	0.52**	0.57**	**0.86**	0.06	0.56	—	—	—	—
5. Responsible AI	0.09	0.11	0.16†	0.1	**0.92**	0.21	—	—	—	—
6. Performance	0.71**	0.51**	0.53**	0.58**	0.25*	**0.75**	—	—	—	—
7. Industry	–0.12	–0.01	–0.05	–0.12†	0.05	–0.12†	NA	—	—	—
8. Age	–0.09	0.12	0.05	–0.04	0.08	–0.13†	0.06	NA	—	—
9. Size	–0.06	–0.07	–0.09	–0.07	0.04	–0.05	–0.04	0.49*	NA	—
10. Operational market	0.14†	0.13	.16†	0.03	0.05	0.03	0.01	0.14†	0.05	NA

Notes: The diagonal values represent the square roots of AVE values. Below-diagonal are correlations between the constructs; above-diagonal (in grey) elements are the HTMT ratio.
†p < 0.10; *p < 0.05; **p < 0.01.

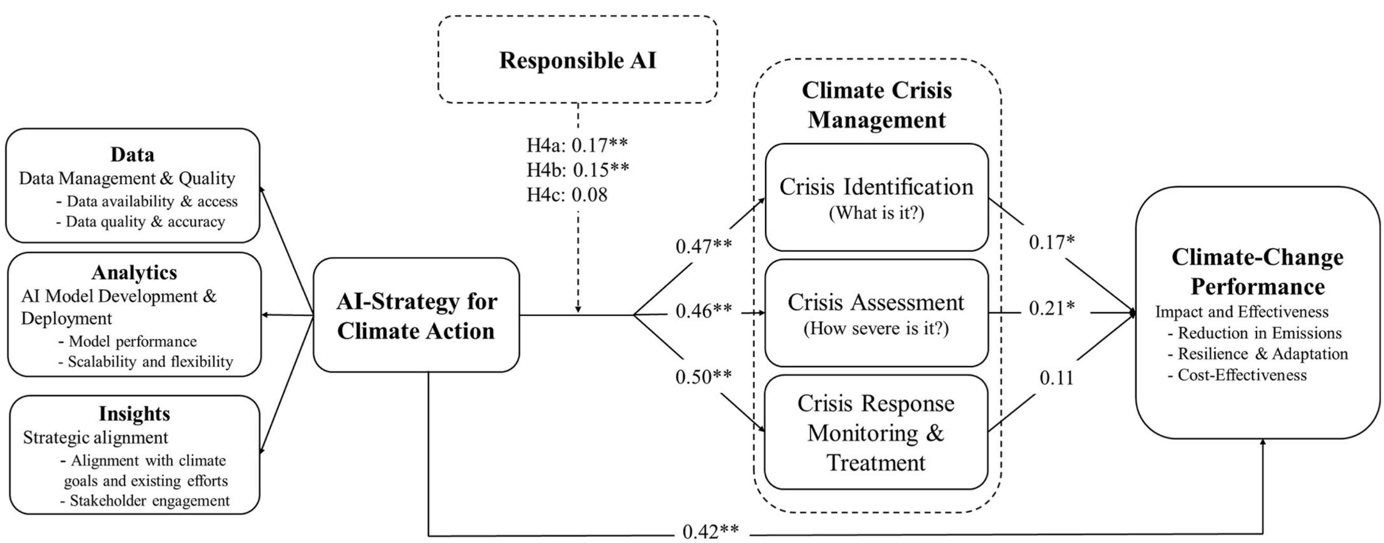

Fig. 2. Structural model results.

5. Discussion and conclusion

This study explores how AI strategies contribute to climate crisis management (CCM) and influence overall climate change performance, guided by two key research questions: (1) How do AI strategies impact CCM and, consequently, climate change performance? and (2) What role does responsible AI play in moderating this relationship? Our findings provide new insights into the effectiveness of AI across various components of CCM, namely risk identification, risk assessment, and crisis response. Specifically, AI strategies significantly strengthen both risk identification and assessment, which in turn lead to improved climate change performance. However, while AI also contributes positively to crisis response monitoring and treatment, this effect does not translate into measurable performance gains. This discrepancy reveals a critical insight: AI is currently more effective in anticipatory, data-driven processes than in managing dynamic, real-time crisis response activities.

This asymmetry can be attributed to the differing operational demands of each CCM stage. Risk identification and assessment are

Table 4
Structural model path estimates.

Variables	Crisis Identification		Crisis Assessment		Crisis Response		Performance	
	β	SE	β	SE	β	SE	β	SE
Main effects								
AI strategy	0.47**	0.06	0.46**	0.07	0.50**	0.07	0.42**	0.07
Climate crisis identification							0.17*	0.05
Climate crisis assessment							0.21*	0.06
Climate crisis response							0.11	0.07
Moderating variable								
Responsible AI	0.05	0.05	0.06	0.05	0.02	0.04		
Interaction effect								
AI strategy × Responsible AI	0.17**	0.05	0.15**	0.05	0.08	0.05		
Controls								
Industry	0.01	0.15	−0.02	0.11	−0.07	0.13	−0.07	0.11
Age	0.22**	0.09	−0.02	0.09	0.04	0.08	−0.15†	0.07
Size	−0.11†	0.04	0.03	0.05	−0.03	0.05	0.08	0.03
Operational market	0.04	0.15	0.09	0.16	−0.04	0.13	−0.03	0.11
R^2	0.30		0.27		0.27		0.56	

Notes: †p < 0.10; *p < 0.05; **p < 0.01.

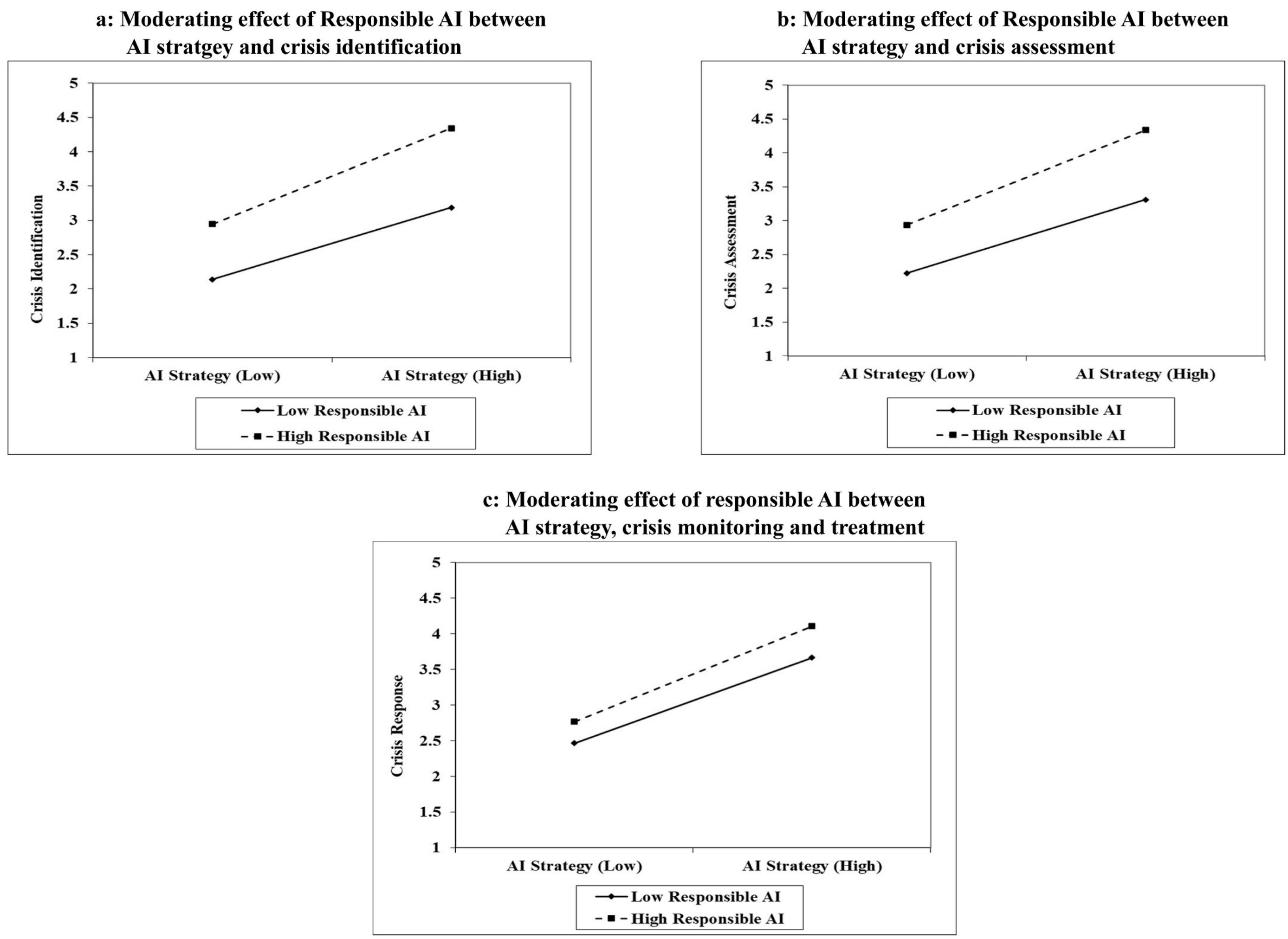

Fig. 3. (a): Moderating effect of Responsible AI between AI strategy and crisis assessment. (b): Moderating effect of Responsible AI between AI stratgey and crisis identification. (c): Moderating effect of responsible AI between AI strategy, crisis monitoring and treatment.

relatively structured tasks that align closely with AI's capabilities in predictive modeling, pattern recognition, and scenario analysis. Organizations can utilize historical and environmental data to detect potential threats and allocate resources proactively (Gupta et al., 2022; Akter et al., 2024). In contrast, crisis response unfolds in fast-paced, unpredictable environments where AI's value may be limited by factors such as incomplete or delayed data, challenges in real-time interpretation, and the need for complex, context-sensitive decisions that often require human intervention (Singh and Goyal, 2023). This highlights the importance of tailoring AI applications based on the specific

Table 5
Conditional effects at different levels of responsible AI.

AI strategy → Crisis identification → Climate change performance				
Responsible AI	B	SE	95 % LL CI	95 % UL CI
−1 SD	0.06**	0.03	0.01	0.15
Mean	0.10**	0.03	0.02	0.19
+1 SD	0.15**	0.05	0.03	0.26
Difference (MM Index)	*0.03***	*0.01*	*0.01*	*0.06*
AI strategy → Crisis assessment → Climate change performance				
Responsible AI	B	SE	95 % LL CI	95 % UL CI
−1 SD	0.05*	0.03	0.01	0.13
Mean	0.09*	0.04	0.02	0.18
+1 SD	0.13*	0.05	0.03	0.24
Difference (MM Index)	*0.02**	*0.01*	*0.01*	*0.05*
AI strategy → Crisis response → Climate change performance				
Responsible AI	B	SE	95 % LL CI	95 % UL CI
−1 SD	0.09**	0.04	0.04	0.16
Mean	0.11**	0.04	0.05	0.17
+1 SD	0.13**	0.05	0.06	0.21
Difference (MM Index)	*0.01*	*0.01*	*−0.01*	*0.04*

Note: MM: Moderated mediation.
†$p < 0.10$; *$p < 0.05$; **$p < 0.01$.

demands of each stage in the climate risk management cycle.

Although previous research has emphasized the role of AI in environmental monitoring and analytics (Kumar et al., 2024b), our study addresses a critical gap by situating AI within a comprehensive CCM framework. Prior studies often treat AI as a standalone tool rather than examining its strategic integration with organizational resilience objectives (Cowls et al., 2023; Nishant et al., 2020). Our results not only confirm AI's effectiveness in enhancing early-stage risk management but also reveal its limitations in crisis response execution. These findings call for more nuanced, context-aware applications of AI in climate strategy, particularly in areas requiring agility, real-time adaptation, and cross-functional coordination.

Furthermore, the literature on responsible AI in the climate change context is still evolving. There is an increasing need for frameworks that ensure AI strategies are ethical, transparent, and inclusive (Kanungo et al., 2024; Liu et al., 2022; Tutun et al., 2023). Our findings indicate that responsible AI plays a crucial moderating role in strengthening the relationship between AI strategy and both risk identification and risk assessment. This suggests that organizations adopting responsible AI principles can maximize the effectiveness of their AI-driven risk management efforts. However, our results also show that responsible AI does not significantly moderate the relationship between AI strategy and crisis response monitoring and treatment, further reinforcing the notion that AI's role in crisis response may require additional refinement to achieve measurable improvements in climate change performance.

While prior studies have acknowledged AI's potential to enhance organizational performance in climate change contexts, empirical evidence on AI strategies' direct impact on climate change performance–particularly in terms of cost-effectiveness, resilience, and sustainability–remains limited (Singh and Goyal, 2023). Our study provides empirical support for AI strategy as a driver of climate change performance through effective risk identification and assessment. Moreover, our moderated mediation analysis reveals that the positive indirect effects of AI strategy on climate change performance via risk identification and risk assessment are amplified when responsible AI is integrated. However, this effect is not observed for crisis response monitoring and treatment, suggesting that further research is needed to explore how AI-driven crisis response mechanisms can be optimized for better climate performance outcomes. One possible reason for this finding is that while AI excels at identifying and assessing risks through predictive modeling and data analytics, its application in real-time crisis response may be hindered by factors such as data reliability, decision latency, and the complexity of dynamic crisis environments (Nishant et al., 2020; Singh and Goyal, 2023). Unlike structured risk identification and assessment, which rely on historical and predictive data, crisis response requires rapid decision-making, coordination across multiple stakeholders, and adaptive learning from unfolding events—areas where AI still faces challenges due to limitations in real-time data processing and interpretability (Gupta et al., 2022; Khalilpourazari and Pasandideh, 2021).

Additionally, AI-driven crisis response mechanisms often depend on external factors, such as infrastructure readiness, regulatory policies, and human expertise, which may influence their effectiveness in mitigating climate-related disasters (Leal Filho et al., 2022). Future research should explore how AI strategies can be enhanced with advanced real-time analytics, integration with human decision-makers, and adaptive learning models to improve crisis response monitoring and treatment, ultimately maximizing AI's impact on climate change performance. Our research contributes to a more comprehensive understanding of AI's strategic role in climate crisis management, emphasizing the importance of responsible AI in enhancing its effectiveness. While our results are grounded in SDG 13, the underlying premise that AI strategies require granularity and contextual adaptation can be extended to other SDGs such as clean water (SDG 6), sustainable cities (SDG 11), and responsible consumption (SDG 12). Future research should explore how AI frameworks, tailored for specific goals, can support broader sustainable development efforts.

Finally, we included industry type (i.e., service or manufacturing) and operational market (i.e., B2B or B2C) as control variables in our model. Our results indicate that these control variables did not have a significant relationship with the CCP constructs. These findings are in line with past research that has demonstrated that AI can be applied effectively across various industries to address climate challenges (Global Partnership AI, 2021; Mondal et al., 2024). For example, AI-driven solutions have optimized irrigation and reduced water usage in agriculture, enhanced energy efficiency in manufacturing, and lowered emissions through route optimization in transportation. These applications show that AI's benefits are not confined to a single sector. Hence, while industry-specific guidelines are important, the overall impact of AI strategies on climate action can be generalized across different sectors and markets.

5.1. Theoretical implications

This study provided four-fold theoretical implications: Firstly, prior literature often treats AI as a tool for automating decision-making processes in climate-related decisions (Hino et al., 2018; Yuan et al., 2020). However, this study conceptualizes AI strategy as a strategic and valuable resource composed of data infrastructure, analytical capabilities, and AI-generated insights (Akter et al., 2021a,b; Shankar and Gupta, 2024). This study emphasizes AI strategy's role in generating, analyzing, and applying environmental data, we demonstrate that AI is not merely an operational tool but a strategic enabler that enhances climate change performance through structured crisis management processes (Arora et al., 2024; Ratten et al., 2024). This research extends prior work by providing empirical support for AI strategy's role in risk identification and assessment, reinforcing the idea that AI must be systematically embedded into organizations' strategic climate agendas to maximize its effectiveness (Broekhuizen et al., 2023; Huang and Rust, 2024).

Secondly, existing crisis management theories emphasize traditional methods of risk assessment and response, which often rely on historical data and reactive decision-making (Farrokhi et al., 2020; Xiao and Yu, 2025). However, this study shifts the perspective by integrating AI into real-time, proactive climate crisis management (Leal Filho et al., 2022; Singh and Goyal, 2023). Our findings suggest that AI significantly enhances an organization's ability to identify and assess climate risks, thereby improving climate resilience and adaptive capabilities (Caner and Bhatti, 2020; Huntingford et al., 2019). While traditional crisis models lack adaptability due to static data limitations (Chen et al., 2023b), AI-based approaches dynamically monitor, analyze, and predict climate risks in ways previously unattainable (Bibri et al., 2024). This theoretical advancement reinforces the importance of AI in enhancing crisis response capabilities while also highlighting its current limitations in crisis response monitoring and treatment, which may require further refinement to achieve measurable performance outcomes (Ghaffarian et al., 2024; Nishant et al., 2020).

Thirdly, while past research has explored AI's role in corporate decision-making, relatively little attention has been given to how responsible AI principles influence AI strategy effectiveness in climate crisis management (Kanungo et al., 2024; Liu et al., 2023). This study draws on the responsible innovation framework (Stilgoe et al., 2020) and provides empirical support for the moderating role of responsible AI, showing that ethical, transparent, and inclusive AI practices significantly strengthen AI's impact on risk identification and assessment but do not significantly enhance crisis response monitoring and treatment (Eitel-Porter, 2021; Voegtlin and Scherer, 2017). These findings contribute to the literature by emphasizing that without responsible AI practices, AI strategies may fail to produce accurate, unbiased, and ethical climate risk assessments (Cowls et al., 2023; Mikalef et al., 2022). Our study highlights that organizations must integrate responsible AI frameworks to enhance the credibility, reliability, and societal acceptance of AI-driven climate solutions (Huang and Rust, 2024; Trocin et al., 2023).

Lastly, sustainability research has long emphasized the need for technological innovations to mitigate climate change, yet studies have predominantly examined AI's role in environmental monitoring rather than its integration into corporate sustainability strategies (Bibri et al., 2024; Leal Filho et al., 2022). This research rooted in the resource-based view theory (Barney, 2001) bridges that gap by positioning AI strategy as a foundational component of corporate sustainability initiatives, showing that firms leveraging AI can not only enhance efficiency but also develop innovative, AI-driven approaches to sustainability challenges (Gama and Magistretti, 2025; Johnson et al., 2022). By demonstrating that AI strategies improve climate change performance through structured risk management processes, our study reinforces the notion that climate resilience must be embedded into corporate AI strategies rather than treated as a secondary goal (Kumar et al., 2024b; Raji, 2024).

Table 6
Managerial Guidelines for AI strategy-based climate crisis management.

AI strategy for climate actions	Climate Crisis Management		
	Climate Risk identification	Climate Risk assessment	Climate change response monitoring & treatment
Data Management & Quality	**Diverse data sources and select sustainability practices:** in identifying the type of risk, it is and accordingly adopt the best sustainability practices in entire firms' value chain and operations *in an ethical and responsible manner*. **Fair access to data:** *Integrate ethics and responsibility in the use of AI data for making equitable and fair access to data and decision making.*	**Timely data collection and communication:** With timely collection of reliable and accurate data through wide sources, firms can *clearly communicate* with the stakeholders for identifying the potential impacts and making agile actions in time for the high-climate risk contexts. **Clear and accessible information:** *Include measures in AI strategies to ensure providing stakeholders with clear and accessible information on potential impacts on value chain operations and stakeholders*.	**Governance:** Continue to manage, record, and retain data *in line with the data governance and ethics regulations* for improved monitoring of trends, and outcomes of specific strategies employed for mitigation. **Verify the reliabilities**: *with environment and climate change specialists for better governance.*
Analytics	**Analysis of scalability and flexibility:** Identify the scalability, adaptability and performance implications to regions and specific climate context (the type of climate crisis). **Fair, equitable and open communication:** *Fair, equitable, and open communication in top down and bottom-up approaches and in analysis of the performance implications of the AI led identified strategic solutions for all the stakeholders.*	**Analysis of the potential of strategic solution**: Under an assessment of a high climate change related risk, analyze the capabilities for dealing that particular climate crisis in a region of operation. Analyze the implications on business operation and value chain activities, and potential for alternative sustainability solutions. **Open communication:** *Open communication regarding the benefits and risks for all stakeholders associated with strategic alternatives for the climate strategies.*	**Analyze the trends and patterns:** Analyze trends and patterns for commitment to climate change sustainability agenda. Adjust the response strategies as climate risks evolve. **Inclusion and governance:** *Analyze the AI policy frameworks for stakeholders' inclusion and governance.*
Insights	**Share, Engage and Collaborate**: Share the insights with all stakeholders timely*, and with accuracy and transparency.* Engage and collaborate with stakeholders in AI led strategic choices for climate change actions. **Ethics and responsibility in value chain:** *Integrate ethics and responsibility in AI driven value chain activities and decisions drawn from the insights.*	**Stakeholder engagement**: Under an assessment of a high climate change related risk, engage and collaborate with market (e.g., customers, suppliers) and non-market (policy makers, technology developers, industry bodies) stakeholders for tackling the climate crisis. **Clear insights on risk distribution**: *Keep transparency in sharing insights and making assessment on how the benefits and risks in climate strategies are distributed among stakeholders.* Under a low climate change risk situation, engage stakeholders, discuss, plan and prepare to minimize the effects. Learn, develop and continue to foster capabilities in line with the technological evolutions and developments.	**Draw insight for continuous monitoring***:* Continue to draw insights for monitoring patterns, policies, strategies and outcomes. **Converse and communicate with stakeholders:** *Continue to clearly converse and communicate the insights with the stakeholders and make the information accessible* to remain agile in climate change-oriented actions. **Other relevant stakeholders:** *Clearly share the monitoring and treatment related insights and make it accessible to key decision makers in climate crisis management strategies for ongoing learning and innovations.* Work with AI technology developers to learn new ways of drawing insights from the AI based data in managing climate crisis, *such the decisions are free from bias, fair and accurate. Managers may consider working with them to ensure that ethical considerations are integrated in AI technologies to support sustainability goals.*

Note1: Italics is used to denote the responsible AI aspects in all cells.
Note 2: The positive indirect effect of AI strategy on climate change performance—mediated through crisis response monitoring and treatment—is stronger at higher levels of responsible AI compared to lower levels. However, this difference is not statistically significant. Despite the lack of significance, the direction of the effect remains positive at higher levels of responsible AI. Therefore, we have included responsible AI in the corresponding cell to reflect its potential relevance for managerial consideration.

5.2. Managerial implications

From practitioners' standpoint, the findings suggest that managers should consider climate change as a part of their AI based strategic actions. Successful implementation of climate risk informed AI strategies can help the firms addressing the climate crisis better, leading to the climate change performance. Using data-derived insights (i.e., based on the findings of this study), Table 6 presents a 3X3 matrix-based guidelines and implications for the managers seeking to achieve climate change sustainability goal specifically with the use of AI-based strategies. The matrix contains the three dimensions of CCM (risk identification, risk assessment, and monitoring and treatment) X three AI strategies for climate actions (data management and quality, analytics, and insights). Within each cell, the specific managerial guidance is provided. Aspects of responsible AI are also integrated for managerial considerations. The matrix can be a guiding tool for the managers in using AI strategy for CCM.

6. Limitations and future research directions

The present study has some limitations that can be tackled in the future studies. From a methods perspective, our study limited to survey-based research. Future studies can adopt a mixed method approach (integrating managerial interviews with surveys) for distilling deeper information regarding types of emergencies firms were facing and specific strategies taken for tackling them. Although we used several techniques—such as question randomization and statistical checks for common method bias—to minimize biases inherent in survey research, our measurement approach may still be subject to item characteristic effects. We encourage future research to adopt alternative strategies, such as collecting data from multiple sources or temporal separation, to further reduce the risk of inflated results due to such biases. Furthermore, a longitudinal perspective can also help capture the overtime effects of AI strategies on CCM. Our study did not consider sector-specific contextualization. Therefore, from a contextual perspective, we suggest studies to explore the findings for the sunset industries that are considered as carbon intensive e.g., oil and gas, mining, petrochemicals (Verrier and Strachan, 2023).

From a theoretical perspective, there are limitations in considering other important aspects of AI implementation. While our study demonstrates the efficacy of responsible AI in strengthening the relationship between AI and CCM, managers continue to face practical challenges related to ethics, governance, algorithmic bias, and data protection (McKinsey, 2018). These challenges become more complex when multiple stakeholders, such as value chain partners, are involved, each with differing capabilities and sustainability goals (McKinsey, 2024a,b). Notably, our finding that responsible AI does not significantly enhance the effect of AI on crisis response monitoring and treatment suggests that firms may need to critically evaluate where responsible AI investments yield the highest strategic value. Future research could investigate under what conditions responsible AI contributes to performance outcomes in crisis response scenarios, and whether such investments are justified beyond direct performance gains—such as reputational benefits, regulatory compliance, or ethical alignment. Specifically, our finding that AI contributes to crisis response monitoring but does not translate into measurable climate performance raises important questions about the conditions and contextual limitations under which AI-driven response strategies become effective. We suggest future research explore how such challenges are addressed by managers across diverse organizational settings. Furthermore, our study did not investigate the specificity of AI strategies at different stages of the value chain (e.g., production, logistics, transportation), where stakeholder engagement and responsibility may vary. New studies can explore how AI data, analytics, and insights operate differently across these stages to support more targeted and effective climate crisis management.

Finally, we acknowledge that Canada and the US have distinct environmental policies and regulatory frameworks. Therefore, future research could build on our findings by exploring how AI strategies impact climate change policies in these two developed countries. Additionally, comparing developed countries with emerging ones would be valuable to understand how different policies affect climate change performance across various countries with different economic contexts. This comparative analysis can offer deeper insights into the effectiveness of AI strategies in diverse regulatory environments and provide tailored recommendations for enhancing global climate action. Comparing the findings between other developed economies such as UK and Australia and emerging economies would allow understanding broader spectrum of AI and climate aspect and enhancing generalizability. Despite no concerns raised regarding reliability, factor loading, validity tests, we acknowledged the limitations of using two-items scales for climate-change performance and encourage future research to extend the work using comprehensive instruments.

In conclusion, our findings provide important insights into the CCM via AI strategies. It also opens avenues for extending the scope of work at the interface of AI and CCM.

CRediT authorship contribution statement

Waqar Nadeem: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Abdul R. Ashraf:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Huda Khan:** Writing – review & editing, Writing – original draft, Conceptualization. **V. Kumar:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization.

Right retention statement

Appendix. Questionnaire items

Indicators	Standardized loadings
AI data management and quality	
1. Our AI strategy ensures access to high-quality and relevant climate data	0.85
2. AI enables us to effectively utilize data from diverse sources (e.g., satellite imagery, IoT sensors, and historical records)	0.72
3. Our AI strategy includes measures to ensure the accuracy, reliability, and timeliness of climate data	0.92
AI analytics	
1. Our AI models developed for climate action are accurate, robust, and reliable	0.83
2. Our AI models are scalable to handle increasing data volumes and computational demands	0.78

(*continued on next page*)

(*continued*)

Indicators	Standardized loadings
3. Our AI models include provisions for adapting models to different geographic regions and climate contexts	0.82
AI-driven insights	
1. Our AI strategy effectively integrates with existing climate action programs and initiatives	0.75
2. The AI projects are coordinated with other sustainability and environmental efforts within the organization	0.78
3. Our AI strategy involves collaboration with climate scientists, policymakers, and other stakeholders	0.86
4. Regular consultations with experts ensure the relevance and accuracy of our AI applications	0.80
Climate crisis identification	
1. Our company regularly uses AI to identify potential climate-related crises	0.89
2. AI helps us recognize early signs of environmental crises that could impact our operations	0.89
3. AI helps us detect vulnerabilities in our supply chain that could lead to crises	0.69
Climate crisis assessment	
1. AI helps us assess the severity and likelihood of climate-related crises	0.82
2. AI helps us analyze the potential impact of environmental crises on our business	0.92
3. AI helps us prioritize climate crises based on their potential impact on our operations	0.91
Climate crisis response monitoring and treatment	
1. AI provides actionable insights for mitigating climate-related crises and continuously monitors operations for warning signs	0.81
2. AI helps us implement effective measures to manage and mitigate crises and provides real-time alerts on potential and ongoing environmental crises	0.90
3. AI technologies are crucial in our crisis treatment and management plans, improving monitoring and communication capabilities	0.87
Responsible AI	
1. Our AI systems are designed to ensure fairness and avoid biases in sustainability decisions	0.89
2. We provide clear and accessible information on how our AI systems operate and make decisions regarding environmental sustainability	0.94
3. Our company is committed to the ethical use of AI in all sustainability operations	0.92
4. Ethical considerations are integrated into the development and deployment of our AI technologies to support sustainability goals	0.92
Reduction in emission	
1. Our AI strategy contributes to measurable reductions in greenhouse gas emissions	0.74
2. Our AI solutions promote energy-efficient practices, resulting in lower operational energy consumption across our business processes.	0.88
Resilience and adaptation	
1. Our AI-driven adaptation strategies are implemented and monitored for effectiveness	0.72
2. Our AI technologies support the development and deployment of early warning systems for climate-related hazards, enhancing community preparedness and response	0.70
Cost-effectiveness	
1. Our AI strategy demonstrates cost-effectiveness in achieving climate action goals	0.84
2. Our AI initiatives streamline operations, significantly reducing waste and optimizing resource use	0.81
Second-order Constructs	
Indicators	**Item loading**
AI strategy	
1. AI data management and quality	0.79
2. AI analytics	0.76
3. AI insights	0.80
Climate change performance	
1. Reduction in emission	0.75
2. Resilience and adaptation	0.80
3. Cost-effectiveness	0.71

Data availability

Data will be made available on request.

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