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Artificial intelligence (AI) for good? Enabling organizational change towards sustainability

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Abstract

Artificial intelligence (AI) is increasingly being recognized as a critical tool when it comes to addressing the most pressing challenges facing modern industries, including the pursuit of sustainability. The use of AI is aiding businesses in navigating corporate sustainability challenges, but existing research lacks a comprehensive exploration of how corporations leverage AI to boost their sustainability. By exploiting an inductive concept-development approach and incorporating data from 24 companies, this study provides valuable insights into the role that AI plays in shaping organizational sustainability strategies, identifying operational enablement and technical capacity as key drivers of AI adoption for corporate sustainability. These drivers are incorporated into the technology, organization, and environment (TOE) framework alongside the strategic steps and capabilities necessary for organizations to effectively adopt and implement AI in the development of their sustainability strategies. Ultimately, this study proposes an integrative model for sustainability-oriented AI adoption that emphasizes the importance of aligning AI initiatives with organizations' sustainability objectives in order to maintain a competitive advantage and drive progress. Correspondingly, it underscores the need for robust data management, system integration, and continual performance monitoring to reduce resistance to AI adoption allowing for the potential of AI to be fully harnessed in pursuit of sustainability. Furthermore, this study offers practical guidance by exploring the direct and indirect use cases of AI in corporate sustainability. The study concludes by highlighting potential avenues for future research in this evolving field.

Keywords Corporate sustainability · Artificial intelligence · Environmental management · Innovation management · Organizational capabilities

JEL Classification O32

1 Introduction

Technological innovation has been pivotal to the development of both business efficiency and global sustainability efforts over the last century (Bickley et al. 2024). Artificial intelligence (AI) has emerged as a particularly transformative technology, often being referred to as the "revolution of the century" (Di Vaio et al. 2020). Recent progress in AI, especially that made in generative AI, has revolutionized communication and data analysis across countless industries, extending far beyond the tech sector. These advancements have sparked rising interest in AI's potential to address critical challenges by, for example, improving corporate sustainability.

In recent years, rules governing sustainability reporting have generally become stricter. In 2021, the European Commission introduced the Corporate Sustainability Reporting Directive (CSRD) with the aim of bolstering these requirements. Today, under the Sustainable Finance Disclosure Regulation (SFDR), organizations must disclose environmental, social, governance, and overall sustainability information, and more detailed reporting will be made compulsory in the years to come. Given the mounting complexity of sustainability-related matters as well as the steady rise in reporting requirements, prior studies have identified AI as having the potential to significantly enhance sustainability and regulatory compliance (Nishant et al. 2020; Vinuesa et al. 2020). AI enhances transparency by analyzing extensive data from various sources to provide real-time insights into supplier practices and, in turn, to facilitate effective monitoring and ensure adherence to human rights and environmental standards (Qu and Kim 2024). To fully harness AI's potential when it comes to sustainability, one must understand its direct and indirect impacts. Its direct impacts stem from applications pertaining to energy efficiency, climate monitoring, waste management, pollution control, and biodiversity conservation (Kalmykov and Kalmykov 2015; Willcock et al. 2018), which give way to notable advantages when it comes to reducing environmental damage and efficiently utilizing resources. Its indirect impacts are broader and less visible, encompassing improved decision-making, behavioral changes, innovation, supply chain efficiency, and heightened public awareness (Domisch et al. 2019; Toivonen et al. 2019).

Despite past research highlighting the potential advantages and innovations that AI could present to corporate sustainability (Kar et al. 2022; Vinuesa et al. 2020), its implementation remains constrained. This lack of action is generally attributed to a lack of awareness and collaboration among internal and external stakeholders regarding AI and sustainability, insufficient organizational capabilities and resources (Arinez et al. 2020; Nishant et al. 2020; van Wynsberghe 2021), and ethical concerns regarding the potential misuse of AI (Heilinger et al. 2024). Nonetheless, the rapid evolution of AI technologies and the mounting complexity of sustainability requirements collectively necessitate immediate guidance on how organizations can effectively integrate AI into their sustainability strategies (Bickley et al. 2024; Wirtz and Müller 2019).

While prior studies have explored AI's potential for corporate sustainability efforts, they have largely focused on specific applications or theoretical implications. For instance, Jorzik et al. (2024) recently proposed a novel AI use case for green technology start-ups that diverged from traditional approaches. However, there is a

severe lack of research that comprehensively and systematically addresses how organizations can implement and scale AI in pursuit of their sustainability goals. Given the recent rapid advancements in AI technology and the associated growth in both the quantity and complexity of corporate sustainability responsibilities, there is a pressing need for solid guidance in order to accelerate the integration and implementation of AI into organizational change (Ahdadou et al. 2024). The main goal of this research is to identify AI's role in enabling sustainability among businesses.

The remainder of this study is structured as follows. First, it details the theoretical background of AI in the field of sustainability. It then describes the research methods employed in its analysis, presents the results, and offers a comparative analysis between this study's findings and those of prior research. Ultimately, this study identifies operational enablement and technical capacity as the key enablers of AI adoption in corporate sustainability efforts. We propose an integrative model for AI adoption in sustainability strategies and develop a framework to address barriers identified by previous studies, offering guidance for practitioners leveraging AI in pursuit of sustainability. Moreover, we point out some of this study's limitations before highlighting some potential paths forward for future research.

2 Conceptual background

2.1 Development of AI technology among corporations

Technology has advanced rapidly in recent years, altering the very ways in which businesses work and create value. In recent years, AI's significant (enabling and inhibiting) influence on both society broadly and businesses in particular (Gupta et al. 2021; Haftor et al. 2021) has made the technology stand out as something with the potential to define the future development of the global economy (Nishant et al. 2020). The term "AI" may be defined as "the use of computational machinery to emulate capabilities inherent in humans, such as doing physical or mechanical tasks, thinking, and feeling" (Huang and Rust 2021). The history of AI can be traced back to the 1950s—the formative years of computer science—but at the start of the twenty-first century, enhanced computational power and greater data quality and accessibility have turned AI into a remarkable tool capable of real-time pattern recognition and learning (Wirtz and Müller 2019). AI today can reduce errors, take over human tasks, and accelerate research (Gupta et al. 2021; Thomas et al. 2024). The surge in AI-related publications over the last five years is indicative of this rapid progress (e.g., Burström et al. 2021; Kanbach et al. 2024; Mariani et al. 2022). This surge presents both challenges and opportunities when it comes to the application of AI across various industries (including critical ones, such as medical solutions and disaster management). Wirtz and Mueller (2019) revealed that AI applications in public management structures have effectively become essential to the exercise of state power and public influence. An AI-driven medical drone overcame critical challenges associated with delivering critical medical supplies during the COVID-19 pandemic and, beyond that crisis, to remote regions (Damoah et al. 2021; Lamptey and Serwaa 2020). In marketing, AI-driven tools like SNAzzy (Social Network Anal-

ysis in Telecom) and VOCA (Voice-of-Customer-Analytics) have bolstered the field of customer analytics (Akerkar 2019). Prior studies have noted AI's influence across multiple sectors as well as its potential benefits in others (e.g., Larsson et al. 2019; Rantala et al. 2023), highlighting the importance of studying AI beyond the confines of specific industries (Gupta et al. 2021).

Although constraints on AI applications remain a topic worthy of investigation, multiple prior studies have highlighted the advantages that AI may offer moving forward in the domain of corporate sustainability (Bickley et al. 2024; Kar et al. 2022). With its power of predictability, AI can be used to identify and predict supply and demand, minimizing production waste, reducing inventory-management overhead costs, and lowering carbon emissions in production processes and throughout supply chains (Arinez et al. 2020; Singh et al. 2022). Moreover, research has shown that AI could enable organizations to achieve up to 79% of the Sustainable Development Goals (SDGs) (Vinuesa et al. 2020).

2.2 Enabling corporate sustainability through AI

Over the last decade, the term “corporate sustainability” has become a significant point of focus for organizational leaders, but the challenges associated with fully integrating sustainability-related factors into organizations still constitute a daunting and complex task (Baumgartner and Rauter 2017; Engert et al. 2016). Corporate sustainability refers to the approach that organizations take to ensure they fulfill their responsibilities to both current and future stakeholders (Dyllick and Hockerts 2002). The concept of corporate sustainability is inherently complex, multidimensional, and subject to rapid change. As a result, it represents a significant challenge for organizations to maintain a high level of corporate sustainability over time (Baumgartner and Ebner 2010; Nguyen and Kanbach 2023). To transition into more sustainable businesses, organizations require a wide range of enabling factors—both internal and external elements ranging from organizational capabilities and infrastructure to business partnerships and local engagements (Annunziata et al. 2018; Dangelico et al. 2017; Fernández-Torres et al. 2024). Multiple prior studies have emphasized technology as a critical component of any drive toward corporate sustainability (Baumgartner and Ebner 2010; Xavier et al. 2020). The potential benefits of AI for corporate sustainability have also garnered significant attention from researchers (e.g., van Wynsberghe 2021; Vinuesa et al. 2020).

Nonetheless, integrating AI into corporate sustainability efforts comes with several challenges, including uncertainty, issues, and barriers (Kar et al. 2022). In the field of social sustainability, for example, data is often qualitative, leading to concerns from both employees and customers about bias, fairness, transparency, and accountability (Köchling et al. 2024; Larsson et al. 2019; López-Torres et al. 2019). On the one hand, businesses must get their customers and employees to be willing participants. On the other hand, businesses face numerous technological challenges associated with AI, such as the need for big data resources, insufficient employee capabilities, high energy demand, and high carbon emissions—all obstacles that must be overcome before AI's benefits can become apparent (Nishant et al. 2020; van Wynsberghe 2021). Furthermore, some have raised concerns regarding the inflation and ambigu-

ity of AI's benefits for sustainability, noting that the technology could ultimately do more harm than help (e.g., Heilinger et al. 2024). Manifold challenges, such as the need for an operating license, the need to gain customer acceptance, and the need for employees with sufficient skills and knowledge, tend to follow similar patterns whenever new disruptive elements, including sustainability initiatives, are introduced into an industry, driving the costs of AI adoption upward (Hahn et al. 2010).

2.3 AI technology adoption in organizations

Tornatzky et al.'s (1983) Technology-Organization-Environment (TOE) framework is a conceptual model in information systems that explains how various factors influence the adoption and use of new technologies (e.g., AI) in organizations (Hradecky et al. 2022; Schwaeke et al. 2024). This model considers the technology's attributes, the organizational context of its implementation, and the external environment in which the organization functions. The TOE framework comprises the three titular elements: technology, organization, and environment. The technology component examines the characteristics of the technology, including its functionality, complexity, compatibility with existing systems, and user-friendliness (El-Haddadeh 2020). The organization component addresses the internal context of the technology's implementation, including the organization's size, structure, culture, and available resources. The environment component conversely addresses the external context, encompassing the market conditions, regulatory requirements, and sociocultural norms that the organization is facing. One of the TOE framework's key strengths is its comprehensive approach to technology adoption and implementation. Instead of concentrating solely on the technology or its organizational context, it more comprehensively recognizes the importance of both internal and external factors in shaping technology adoption and utilization (Baker 2012). However, this framework also has some limitations. For instance, it may fail to fully capture the intricacies of technology adoption and implementation, especially in rapidly changing environments in which external factors can significantly impact technology-related decisions. Additionally, it lacks emphasis on individual and behavioral factors (Oliveira and Martins 2011).

Nonetheless, we employed the TOE framework in this study to conduct a structured analysis and identify potential areas for future research (El-Haddadeh 2020; Tornatzky and Fleischer 1990). Studying the adoption of digital innovation among organizations using a theoretical foundation requires careful consideration of the factors behind the adoption process. Existing research has confirmed that the TOE framework is suitable for analyzing the dynamics underlying organizational adoption (El-Haddadeh 2020), offering scholars and decision-makers a more comprehensive overview of the factors that drive AI adoption in corporate sustainability efforts (Khan et al. 2021). Other frameworks like the technology acceptance model and the unified theory of acceptance and use of technology focus on individual acceptance decisions, but the intricacy and broad scope of organizational technologies require a more comprehensive framework. The TOE framework has been applied in various ways in previous studies, having been used to investigate factors like cost-setting, security concerns, and management support as well as to assess the integration of

organizational factors with theories of innovation diffusion and technology acceptance. These studies have contributed to our current understanding of the factors behind AI adoption in corporate sustainability efforts (Lee and Lee 2014). The TOE framework's ability to structure and integrate different clusters facilitates a comprehensive analysis of technologies' adaptability within an organization. Therefore, we contend that examining the influential factors within the three clusters—technology, organization, and environment—will provide scholars and practitioners with a comprehensive understanding of the current state of the literature on the application of AI to corporate sustainability.

3 Methodology

3.1 Research design

To ensure the thoroughness of this qualitative research, we abided by the Gioia methodology of inductive concept development (Magnani and Gioia 2023), which enables researchers to empirically examine and document phenomena (Gioia et al. 2013; Yin 2014)—in this case, AI adoption in corporate sustainability efforts. This method has been used in and proven to be valuable in previous strategic studies on AI integration (Jorzik et al. 2024). Thus, this qualitative approach is particularly appropriate for this study, as it can extend the existing theory to study how organizations employ AI technology to fulfill their sustainability-related responsibilities and challenges. To comprehensively identify relevant data for our research and offer a cohesive perspective on the application of AI in research on corporate sustainability, we employed thematic analysis, following a pattern-inducing technique to generate concepts from the data (Magnani and Gioia 2023). Initially, we conducted a thorough review in which we identified commonalities among interviews to organize emerging topics into first-order concepts according to Gioia et al.'s (2013) guidelines. These concepts were then aggregated into wider dimensions to reflect the data's overarching themes.

3.2 Data sample

We employed purposive sampling—a strategy that is particularly well-suited for exploratory studies aimed at gathering rich, context-specific insights—to capture a broad range of perspectives on and facilitate the development of AI adoption theory (Patton 2014). Given our focus on how AI facilitates corporate sustainability, our sample selection covered a range of organizational sizes (from those with fewer than 10 to those with over 50,000 employees) and maturity levels (from start-ups to those with over 100 years of operational experience) to achieve a comprehensive understanding of AI use in organizational sustainability efforts. We first constructed a comprehensive list of corporations with a demonstrable interest in AI by consulting various sources, including company websites, press releases, and industry reports. To address the research question fully, we considered firms from a wide range of industries and countries, thereby capturing an equally wide range of approaches to AI-driven corporate sustainability. We then identified and approached managers,

senior managers, and executives within the considered firms who were responsible for and directly involved in AI-related sustainability initiatives (see Table 1 for a summary of the interviewees). In-depth exploratory semi-structured interviews were conducted with each of these officials, centered on four key themes: use cases of AI (including applied tools); approach to AI implementation; AI's contribution to corporate sustainability; and personal reflections on likely future trends of the discussed AI applications. This structure enabled us to gather respondents' insights regarding entrepreneurs' adoption of AI to manage uncertainty. To expand the scope of our data, we employed the snowball sampling technique, whereby interviewees were asked to recommend or invite additional participants who meet the requisite criteria and could contribute valuable information (Biernacki and Waldorf 1981; Bell and Bryman 2007). This approach is consistent with this study's exploratory nature, which was designed to generate novel insights that contribute to theoretical development rather than to achieve a representative sample (Eisenhardt 1989). A total of 24 interviews were conducted and recorded between November 2023 and August 2024, with data

Table 1 Interviewee overview

Respondent	No. of employees	Industry	Respondent's position
R1	5 k	Construction	Head of AI
R2	> 130 k	Service Provider	Manager
R3	> 5 k	Banking	Manager
R4	> 5 k	Manufacturing	Manager
R5	< 10	Consulting	Managing Partner
R6	> 320 k	Health Care	Manager
R7	< 10	Consulting	Managing Partner
R8	> 5 k	Manufacturing	Head of Digital
R9	> 500 k	Retail	Head of AI
R10	> 320 k	Health Care	Manager
R11	> 70 k	Health Care	Manager
R12	> 200 k	Retail	Manager
R13	> 7 k	Insurance	Manager
R14	> 7 k	Insurance	Manager
R15	> 150 k	Insurance	Manager
R16	25	AI Start-up	Manager
R17	< 10	Consulting	Manager
R18	> 100 k	Consulting	Head of AI
R19	> 50 k	Banking	Head of ESG Innovation
R20	> 100 k	Consulting	Head of Sustainability
R21	< 10	Start-up	Managing Partner
R22	> 50 k	Consulting	Manager (ESG)
R23	> 50 k	Banking	Chief Sustainability Office
R24	> 50 k	Crop Science	Head of Sustainability

collection continuing until theoretical saturation—the point at which no new theoretical insights were gained from additional interviews (Corbin and Strauss 1990)—was achieved. Each interview was conducted in line with a structured guide that enabled the interviewers to respond promptly to participants' remarks (Eisenhardt 2007; Guest et al. 2006). The interviews were conducted via digital videoconferencing tools, namely Zoom and MS Teams, and lasted an average of 30 min.

3.3 Data analysis

The Gioia method (Gioia et al. 2013) was instrumental in structuring our coding process, enabling a systematic progression from raw data to refined theoretical constructs. As outlined by Corbin and Strauss (1990), we employed open coding, axial coding, and theoretical coding to distill the data into a cohesive structure. During open coding, we assigned descriptive labels to notable data segments (i.e., interview transcripts) in order to capture the main idea of each piece of information. The interviews were transcribed verbatim, and distinct linguistic and phonetic features were excluded to allow for a sole focus on the substance. Our investigation involved multiple iterations of cumulative coding. Each researcher independently transcribed and coded the data. To enhance the reliability and validity of our findings, the research team held regular discussions on coding and data analysis. We iteratively analyzed the data until recurring patterns emerged and were confirmed through feedback loops. Axial coding facilitated the identification of underlying structures, enabling us to reduce the number of codes and focus on core themes. Finally, theoretical coding allowed for the emergence of higher-level theoretical constructs, giving way to a robust data structure progressing from first-order concepts to second-order themes and aggregate dimensions, as depicted in Fig. 1. We used MAXQDA to obtain a comprehensive overview of the theoretical relationships between the codes, and we used the Gioia method (Gioia et al. 2013) to infer patterns inductively. This iterative comparison strengthened our findings' internal validity, enabling us to refine our theoretical framework based on real-world insights, as recommended by Eisenhardt (1989). This step-by-step interaction between theoretical expectations and empirical observations not only anchored our findings in established theories but also contributed novel insights into how AI enables corporate sustainability.

4 Findings

Following the interviews, we identified use cases for AI in corporate sustainability efforts, encompassing both direct and indirect applications. Additionally, we synthesized the findings from the Gioia analyses (see Fig. 1). Operational enablement and technical capacity emerged from this analysis the two key aggregate dimensions.

4.1 Use cases of AI for ecological sustainability

When examining the application of AI with a focus on environmental sustainability, we uncovered evidence to distinguish between its direct and indirect impacts

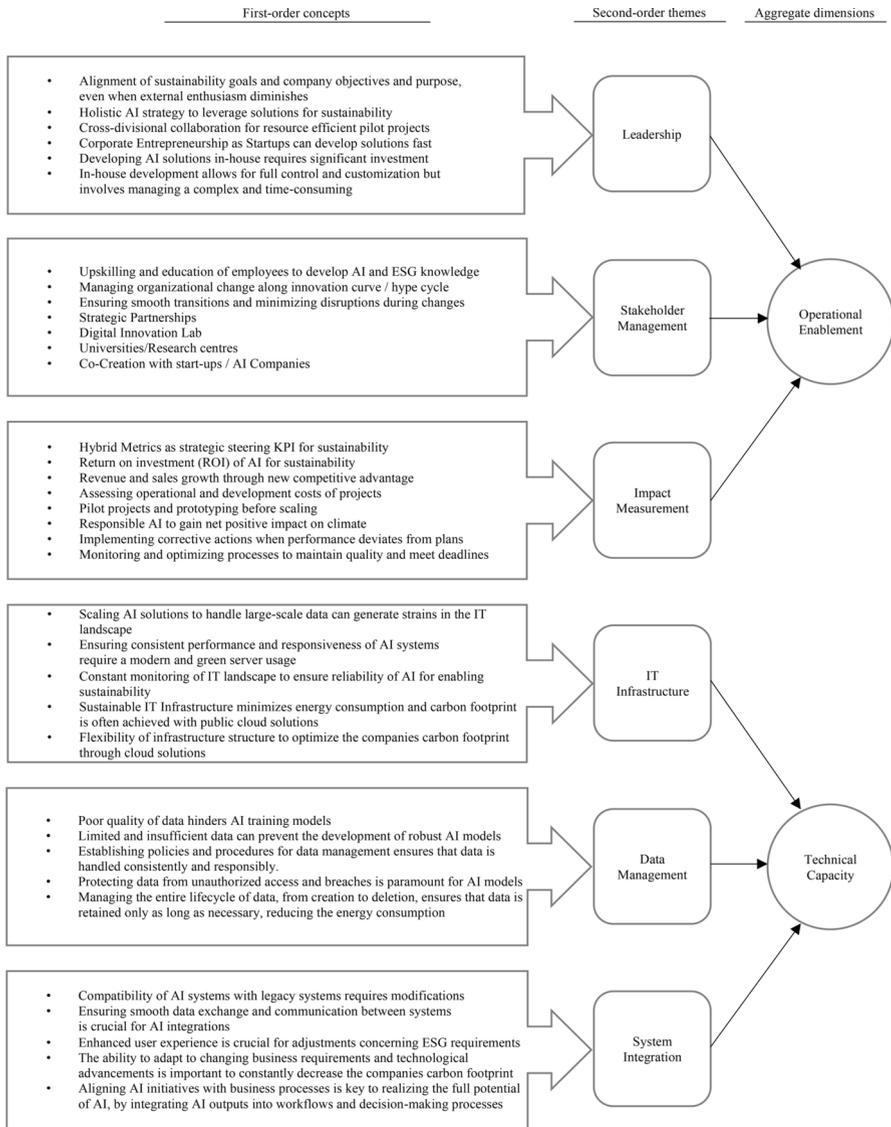


Fig. 1 First order Concepts and Second Order Themes derived from Interview Findings aggregated to two Dimensions for AI Adoption for Sustainability in Organizations

on sustainability efforts. Direct impacts are the immediate and observable effects of AI on environmental sustainability. Applications of AI reduce environmental harm and optimize resource usage. Moreover, they enhance energy efficiency, manage smart grids, and integrate renewables. AI advances climate monitoring by improving forecasts and prediction patterns. In waste management, AI can improve sorting and recycling. It also aids pollution control through real-time monitoring and prediction. Additionally, AI supports biodiversity conservation by tracking wildlife and detect-

ing poaching using cameras or satellite data. Indirect impacts include the less visible ways in which AI contributes to environmental sustainability. Such impacts are often realized through changes in systems, behaviors, or long-term outcomes. For example, AI enhances decision-making by offering advanced analytics and simulations that improve environmental planning and policymaking. By providing insights into the potential impacts of various strategies, AI aids in the development of more effective and sustainable environmental policies. Additionally, AI-driven applications can influence consumer behaviors toward more sustainable choices; recommendation systems on e-commerce platforms can promote products with lower environmental footprints, while apps can encourage individuals to reduce their energy consumption through personalized tips and feedback. AI also fosters innovation and research in environmental technologies by accelerating the development of new materials that can reduce carbon emissions or optimize sustainable agriculture processes. These innovations often lead to cascading effects on sustainability. Supply chain optimization is another area to which AI contributes indirectly. By predicting demand and optimizing logistics, AI enhances supply chain efficiency, which translates to reduced emissions from transportation and manufacturing. Lastly, AI solutions can significantly enhance transparency, boosting compliance with sustainability regulations (e.g., European Sustainability Reporting Standards) by leveraging advanced data-analysis and -reporting capabilities while reducing the manual effort required for compliance documentation, minimizing the risk of errors, and ensuring that reports align with regulatory standards. By improving data accuracy and report-generation efficiency, AI helps organizations to more effectively meet regulatory requirements while enhancing overall operational efficiency.

4.2 Operational enablement

4.2.1 Leadership

While AI can enhance sustainability reporting and decision-making, it entails the navigation of complex and uncharted territories, which may not always lead to immediate success. R16 observes a broader societal trend whereby interest in sustainability, particularly among younger generations, appears to be waning. This decline could negatively affect the willingness of organizations to invest in sustainability initiatives. To counter this, R17 emphasizes the need for long-term goals that ensure that organizations remain committed to sustainability even when external enthusiasm fades.

The excitement surrounding AI has followed a familiar pattern seen with many technological innovations. Gartner's "hype cycle" outlines the stages that emerging technologies generally go through from their initial development to their eventual mainstream adoption. Initially, novel technologies generate significant enthusiasm, leading to the "peak of inflated expectations," where over-optimism and unrealistic projections dominate discourse. However, as technical challenges, limitations, and complexities surface, the initial enthusiasm diminishes, resulting in a descent into the "trough of disillusionment" (Fenn and Raskino 2008). The key to harnessing the transformative potential of any technological innovation lies in successfully navigat-

ing past this descent. Only through sustained effort and adaptation can technologies then ascend the "slope of enlightenment," where their capabilities come to be pragmatically understood, and eventually reach the "plateau of productivity," where they achieve broad utility and deliver tangible benefits. Overall, overcoming the initial post-enthusiasm frustration is critical to the use and long-term viability of sustainability-oriented AI (Interviewee R24).

AI's potential to transform sustainability practices is vast, but realizing this potential will require more than just investment in technology. Interview insights reveal that it will require the prioritization of sustainability and the alignment of AI initiatives with long-term organizational goals. However, R17 also asserts that there is a degree of reluctance among many companies to fully embrace comprehensive sustainability reporting practices. They often resort to mimicking competitors rather than developing authentic strategies. This trend indicates a disconnect between the immediate pressures of business operations and the long-term aspirations of sustainability. R20 and R17 argue that AI has the potential to bridge this gap, providing organizations with the tools necessary to genuinely integrate sustainability into their core business strategies.

4.2.2 Stakeholder management

The successful integration of AI into sustainability strategies requires the careful management of internal stakeholders. R17 highlights the importance of education to mitigate fear and resistance among users. The introduction of AI is often met with apprehension, particularly among employees unfamiliar with the technology. To address this, organizations must invest in a comprehensive upskilling strategy featuring training programs that not only educate employees on the technical aspects of AI but also emphasize its role in promoting sustainability and securing the organization's future. Overseeing organizational change is also vital, as there are many concerns about efficiencies being replaced by AI. R21 underscores the need for a structured approach to change management that ensures smooth transitions and minimizes disruptions. This involves engaging in clear communication, setting realistic expectations, and involving employees at all levels in the change process. By fostering a culture of openness and adaptability, organizations can mitigate resistance and ensure that AI-driven sustainability initiatives are embraced across the board.

In the context of AI-driven sustainability efforts, the integration of effective onboarding and ongoing skill development is paramount when it comes to the successful adoption of new technologies and the achievement of environmental objectives. Comprehensive training programs ensure that employees are well-equipped with skillsets that align with their organization's strategic goals. Furthermore, cultivating a culture of lifelong learning and implementing recognition systems incentivize employees to actively engage and contribute to sustainability efforts.

To maximize the impact of AI on sustainability, organizations must also engage external stakeholders through strategic partnerships and collaboration with digital innovation labs, universities, research centers, and start-ups. These partnerships enable organizations to tap into cutting-edge research, access new technologies, and co-create innovative solutions that drive sustainability.

Moreover, collaborations with industry leaders and specialized firms can provide organizations with the expertise needed to implement complex AI-driven sustainability projects. These partnerships are essential for scaling initiatives and ensuring that they are aligned with the latest technological advancements and sustainability standards. By engaging with digital innovation labs, organizations can experiment with new AI technologies within a controlled environment. These labs provide a space in which to test and refine potential AI applications before deploying them at scale, reducing the risk of failure and ensuring that the technology is fully optimized for the pursuit of sustainability goals. Academic partnerships are crucial for advancing AI-driven sustainability research. Universities and research centers can provide the theoretical foundations and empirical data necessary to develop robust AI models. Additionally, these institutions can offer insights into emerging trends and potential future applications of AI in corporate sustainability efforts. Collaborating with start-ups enables organizations to leverage the agility and innovative spirit of smaller, more flexible entities. Start-ups often bring fresh perspectives and are more willing to take risks, making them ideal partners for the co-creation of new AI-driven sustainability solutions. These collaborations can lead to the rapid development and deployment of cutting-edge technologies that larger organizations may be slower to adopt.

One of the primary advantages of partnering with start-ups is the potential for rapid innovation. Start-ups can develop and deploy solutions quickly, enabling organizations to bring new sustainability initiatives to market faster than they could developing them in-house. If speed is a critical factor, "buying" or partnering with a start-up may be the preferable option. Furthermore, in-house development can be resource-intensive, requiring significant investment in technology, talent, and time. Start-ups, on the other hand, may already have developed specialized solutions that can be acquired or licensed at a lower cost. This straightforward "buy" option can be more cost-effective, especially for organizations that lack the necessary resources or expertise to develop the technology internally. The "make" option, however, enables organizations to maintain full control over the development process, ensuring that the AI solution is fully tailored to their specific sustainability goals. However, this control comes with the need to manage the entire development lifecycle, which can be complex and time-consuming. Organizations must weigh these risks against the potential benefits. By partnering with or acquiring start-ups, organizations can infuse their sustainability strategies with new ideas and technologies that drive future growth. The "buy" option can be particularly attractive for companies looking to stay ahead of the curve and adapt innovations in a fast-paced manner in their sustainability efforts. The decision to make or buy also depends on the strategic fit between the organization and the start-up. If the start-up's vision, culture, and goals align closely with those of the organization, a partnership or acquisition may be more successful and sustainable in the long term. Conversely, if they lack such alignment, it may be more practical to develop the solution internally.

4.2.3 Impact measurement

Incorporating AI into sustainability initiatives can grant competitive advantages to companies, but the financial performance and ongoing performance monitoring of such projects play crucial roles in determining their success and scalability.

Financial performance is critical to the success of AI-driven sustainability initiatives. Maintaining liquidity, ensuring strong ROI, driving revenue growth, and managing costs all empower companies to leverage AI in pursuit of their financial and environmental goals. Adequate liquidity and stable cash flow are essential for sustaining these projects, which often require significant upfront investments. Proper financial management ensures continual funding and scalability, while a strong ROI justifies the adoption and expansion of AI initiatives, attracting further investment and support.

A thorough assessment of operational and development costs is vital to the financial success of AI in sustainability projects. Such an assessment would cover the many costs associated with AI development (e.g., data acquisition, algorithm training, ongoing maintenance) and integration. Companies must weigh these costs against potential savings and benefits to ensure that the project is financially sustainable. A clear understanding of these expenses enables better budgeting, resource allocation, and long-term planning.

Before fully scaling AI-driven sustainability initiatives, it is important to conduct pilot projects and prototyping. These smaller-scale implementations allow organizations to test AI models, identify potential challenges, and refine strategies without making extensive commitments. Performance monitoring during this phase helps to validate the feasibility and effectiveness of AI solutions, providing valuable insights that inform larger rollouts. By learning from pilot projects, companies can increase their chances of success when it comes to scaling up their operations. This ensures feasibility and highlights AI's iterative capabilities, which is a fresh and practical approach to sustainability.

Ongoing progress monitoring against predefined sustainability goals is essential to ensure that AI initiatives stay on track. Regular performance assessments help to measure the impact of AI on, for example, carbon emissions and resource-use efficiency. Such assessments allow organizations to evaluate strategies, make informed decisions, and showcase progress to stakeholders. Performance monitoring also aids in the identification of deviations and the implementation of corrective actions, ensuring that projects remain effective and aligned with organizational objectives. By optimizing processes and tracking KPIs, organizations can maintain a high level of quality, meet deadlines, and efficiently achieve their sustainability goals.

The increasing relevance of these metrics is driven by the need to move beyond philanthropy-oriented approaches to substantiate sustainability efforts with quantifiable data that resonates within the business world. The concept of hybrid metrics involves combining impact metrics (which measure environmental and social outcomes) with financial metrics (which track economic performance). This integration is crucial for making sustainability initiatives credible and actionable within the corporate environment. Implementing hybrid metrics entails overcoming significant challenges, such as integrating diverse data sources and ensuring data accuracy (Inter-

viewee R20). For example, in the banking sector, understanding the environmental and social impact of investments requires detailed insights into client operations, which are often lacking. Developing methods to gather and analyze these data effectively is essential. AI tools can significantly enhance the development and application of hybrid metrics, as they can process vast amounts of data, reveal insights, and automate the analysis of impact and financial metrics. This capability aids organizations in simplifying complex data, improving accuracy, and providing actionable insights (Interviewee R20).

4.3 Technical capacity

The success of AI-driven sustainability initiatives hinges not only on innovative algorithms and data insights but also on robust and efficient IT infrastructure. As organizations integrate AI into their sustainability strategies, they must address the unique challenges and demands associated with AI-based technologies.

4.3.1 IT infrastructure

Sustainability-oriented AI solutions often entail the processing and analysis of vast amounts of data derived from environmental sensors, supply chains, and energy grids, among other sources. Scaling such systems to handle large-scale data can put significant strain on IT infrastructure. Without adequate capacity and processing power, AI models may struggle to perform effectively, leading to delay, inefficiency, and inaccuracy. A well-designed IT landscape that can scale dynamically is essential to ensure that AI applications can process and analyze data at the necessary speed and scale, enabling organizations to achieve their sustainability goals. For AI systems to deliver reliable and timely insights, they must be responsive and consistent in their operations. This demands a modern IT infrastructure that not only supports high-performance computing but also incorporates green, energy-efficient technologies. By leveraging eco-friendly servers, optimized data centers, and energy-efficient networking, organizations can reduce the carbon footprint of their AI operations while maintaining the necessary computing power. This approach aligns with the dual objectives of achieving sustainability through AI and minimizing the environmental impact of the IT infrastructure.

4.3.2 Data management

The quality and quantity of data directly influence the performance and reliability of AI models, making robust data-management practices a priority for organizations. AI models rely heavily on the quality of the data used for training. Low-quality data featuring inaccuracies, inconsistencies, missing values, or biases can significantly hinder the effectiveness of AI systems. When data quality is compromised, AI models may produce unreliable or flawed predictions, leading to ineffective decisions and poor sustainability outcomes. Ensuring high data quality through rigorous data cleaning, validation, and governance practices is essential to the development of AI models capable of delivering accurate and actionable insights. The development of

robust AI models requires access to comprehensive and diverse datasets. Limited or insufficient data can prevent AI systems from capturing the full complexity of the environmental, social, and economic factors involved in sustainability. Without enough data, AI models may struggle to generalize across different scenarios, leading to incomplete or biased analyses. To overcome this challenge, organizations can invest in data-collection and integration strategies that bring together diverse data sources, facilitating the creation of AI models that are both robust and capable of driving meaningful sustainability outcomes.

4.3.3 System integration

To fully leverage AI's potential, organizations must ensure that their AI systems can seamlessly integrate with existing IT infrastructure and communicate effectively with other systems. The organizations behind every interviewee in this study operate legacy systems that are deeply embedded in their operations. Integrating new AI solutions within these legacy systems can be challenging, as they may not be inherently compatible. Modifications and updates are often necessary to bridge the gap and ensure that AI can be effectively deployed without disrupting existing workflows. Organizations must address compatibility issues to harness the power of AI while maintaining operational continuity. Additionally, for AI systems to drive meaningful sustainability outcomes, they must be able to communicate smoothly and exchange data with other systems within the organization, including not only legacy systems but also other AI models, databases, and external data sources. Seamless data exchange is crucial to facilitate real-time processing and analysis. Effective system integration ensures that data flows freely across the organization, enabling AI to deliver accurate insights and support sustainability goals without being hindered by technical bottlenecks or data silos.

4.4 Integrative model for sustainability-oriented AI adoption

Drawing on the insights gathered from the interviews in the previous section and concepts from Stouten et al. (2018) and Tornatzky and Fleischer (1990), we have developed a framework with which to leverage AI to enhance organizational sustainability. This framework explores the central themes of AI integration in corporate sustainability and proposes a structured approach to overcoming barriers identified by prior research.

Figure 2 visualizes this framework. Using the TOE framework as its foundation, it considers external, technological, and organizational factors behind successful implementation. The environmental aspect of the TOE framework influences the identification of potential AI use cases in corporate sustainability efforts. In this context, the environmental aspect (which consists of government regulations and market structure and characteristics) has been expanded to include external stakeholder management (Tornatzky and Fleischer 1990). With regard to sustainability, many companies have underrated the value of public opinion (Parguel et al. 2011). In the capabilities step, an organization assesses its operational enablement and technical capacity, addressing deficiencies as needed. Accordingly, the organizational com-

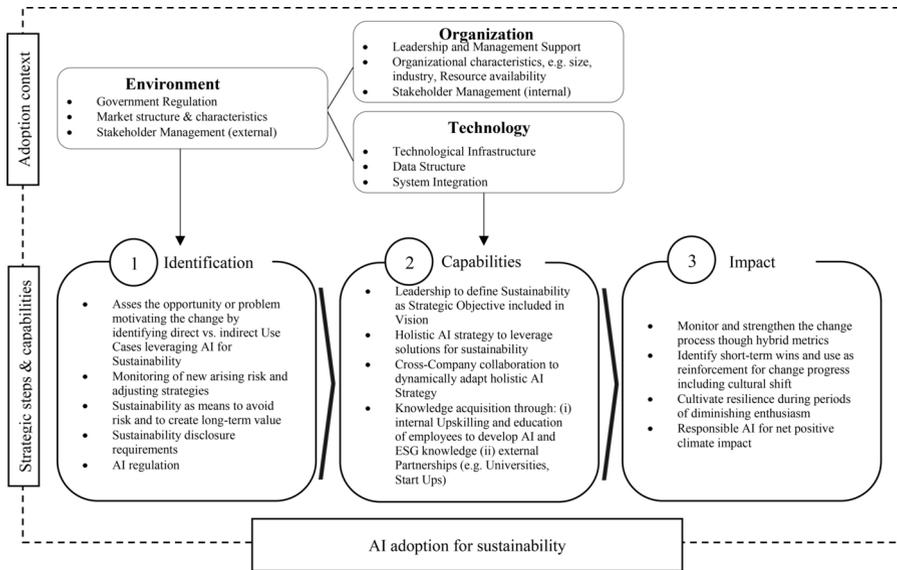


Fig. 2 Strategic Steps and Capabilities for Organizational Adoption of AI technology for Sustainability (own figure in reference to Stouten et al. 2018; Tornatzky and Fleischer 1990)

ponent of the TOE framework (comprising organizational characteristics like size, industry, and available resources) has been augmented by the inclusion of leadership and management support. The results of our data analysis have demonstrated that this is of great consequence when it comes to the adoption of AI for the purpose of driving corporate sustainability. The technology aspect of the TOE framework has been augmented through the incorporation of second-order themes (namely IT infrastructure, data structure, and system integration). It is incumbent upon organizations to address the challenges and demands that AI-driven technology places upon them. To maintain a robust and efficient IT infrastructure, organizations must ensure the cleanliness of the data structure and processes within software applications as well as the seamless exchange of data across the company-wide IT landscape through fully integrated systems. The framework broadens the existing literature by incorporating impact measurement as a dimension behind technology adoption. Moreover, it expands the strategic steps, as proposed by Stouten et al. (2018), available to organizations looking to adopt AI to improve their sustainability. Organizations start by identifying the opportunities, risks, and regulatory requirements associated with aligning AI with their sustainability goals. Key capabilities include the prioritization of sustainability, cross-functional collaboration, and stakeholder management for upskilling and partnerships. The next phase involves developing infrastructure for AI adoption, focusing on risk management, and fostering an innovative culture. An additional step that this study showcased was impact measurement, which includes monitoring progress, achieving short-term wins, and fostering resilience. Overall, the framework stresses the need for responsible AI practices to ensure that the technology has positive impacts on the climate, in line with evolving environmental and

Table 2 Theory enhancements for integrating AI for the purposes of corporate sustainability

Finding areas	Finding key elements	Contributions and implications	Findings in the literature	Theory enhancements
Stakeholder Management	Internal Stakeholder	Upskilling and change management Awareness enhancement	Issue of information asymmetry and bias of human emotions (Cullen-Knox et al., 2017) AI acceptance and adoption (Mariani et al. 2022)	Findings elaborate further on the meaning process to introduce AI and motivate the application of AI in sustainability
	External Stakeholder	External stakeholder engagement and collaboration	Stakeholder management in sustainability (Kar et al. 2022; Torelli et al. 2020)	
Leadership	Purpose and Objectives	Incorporation of sustainable AI into long-term vision	Sustainable AI constraint (Akerkar 2019; van Wynsberghe 2021)	Findings emphasize the essential driver behind the integration of AI into sustainability and the ways in which this driver could be maintained
	Strategy Management	Incorporation of AI into corporate sustainability strategy		
Technical Capacity	Building AI-oriented IT infrastructure Enhancing Data Management	Infrastructure required for AI (Nishant et al. 2020)	Sustainable Innovation capabilities (Kodama 2017; Li 2017) AI application in innovation (Haefner et al. 2021)	The findings improve our existing knowledge on technological constraints and capacity to overcome the limitations of AI usage in the sustainability sector and suggest means of implementing AI
Impact Measurement	Financial Management	Long-term financial KPI for AI-strategy management	AI Project management (Larsson et al. 2019) Lack of transparency and accountability (Larsson et al. 2019)	Findings address the concerns raised in prior studies regarding the low requirements for sustainable AI management through hybrid metrics and dynamic adjustment via performance monitoring
	Performance Management	Metrics for sustainable AI	Lack of performance measurement for AI in sustainability (Braccarense et al. 2022)	

regulatory demands. By integrating TOE principles, this framework guides organizations in deploying AI strategically to bolster their long-term sustainability.

5 Discussion

5.1 Theoretical implications

This study's findings validate and extend the established literature, its theoretical enhancements summarized in Table 2. The insights derived from this research offer a comprehensive understanding of organizational capabilities, leadership, technical infrastructure, and performance measurement.

5.1.1 Organizational capabilities

The findings reveal a consistent pattern among organizations, emphasizing the critical role that organizational capabilities and resources play in facilitating AI adoption for corporate sustainability. AI's true value in this field lies in its ability to configure solutions tailored to complex organizational structures, processes, and cultures (Akerkar 2019; Russell and Norvig 2003). By addressing the social dynamics of AI adoption (particularly in sustainability contexts), this study's findings illuminate how resistance and misunderstanding among employees can hinder progress. This finding builds on the challenges of information asymmetry and emotional biases, highlighted by Cullen-Knox et al. (2017), and broadens the discourse on AI acceptance and adoption (e.g., Mariani et al. 2022). The findings also emphasize the importance of risk management in the facilitation of widespread AI adoption. Mistrust and skepticism regarding the technology's potential misuse and lack of control are significant barriers (Mariani et al. 2022). These concerns are particularly acute in social sustainability contexts, where AI misuse can lead to genuine ethical or societal harm (Heilinger et al. 2024). Notably, this study uncovered evidence indicating that robust risk-management frameworks can bolster trust among employees and external stakeholders, addressing the AI integration gaps identified by Heilinger et al. (2024). Such frameworks not only equip employees with the skills and knowledge necessary to prevent misuse of AI but also align well with general organizational sustainability strategies (Shad et al. 2019). Moreover, this study's findings underscore the critical role played by external stakeholder engagement and collaboration; effective stakeholder management ensures broad support for AI-driven sustainability strategies, echoing the findings of Kar et al. (2022) and Torelli et al. (2020). Finally, in line with organizational change models (Sroufe 2017; Stouten et al. 2018) this study's findings highlight the importance of collaboration in efforts to address complex sustainability challenges.

5.1.2 Leadership and strategic vision

Leadership commitment represents a primary driver of AI adoption, as it facilitates sustained efforts to embed sustainability into organizational practices. These findings expand on the constraints identified by Akerkar (2019) and van Wynsberghe (2021), offering actionable insights into how visionary leadership can address risks and promote sustainable outcomes. The importance of leadership in sustainability-oriented change efforts has consistently been emphasized by prior research (e.g., Lozano 2015; Silvestre et al. 2018). For AI-driven sustainability initiatives, the findings stress the need for long-term strategies that actively support organizational changes until they are fully realized (Kar et al. 2022). While earlier studies explored AI's role in innovation (Haefner et al. 2021), this study's findings highlight the importance of aligning AI initiatives with holistic, long-term sustainability objectives, moving beyond ad hoc projects.

5.1.3 Technical infrastructure and innovation capabilities

This study demonstrated that building AI-oriented IT infrastructure and bolstering data-management capabilities are critical technical prerequisites for sustainable AI implementation. These findings align with previous research on infrastructural requirements (e.g., Nishant et al. 2020) and sustainable innovation capabilities (e.g., Kodama 2017; Li 2017). Furthermore, they expand the literature by addressing unique constraints and opportunities within the sustainability sector and widening the applicability of the TOE framework in a new organizational context, that being corporate sustainability efforts (Tornatzky et al., 1983).

5.1.4 Performance measurement and financial oversight

This study's findings address gaps in existing performance measurement and financial management frameworks for sustainable AI. Long-term key performance indicators (KPIs) are essential when it comes to transparency and accountability in AI project management (Larsson et al. 2019). In fact, metrics with which to evaluate sustainability in AI initiatives have previously been identified as a key area where existing gaps in performance measurement (Bracarense et al. 2022) must be addressed. This study's findings advocate for standardized frameworks to measure AI's impact on sustainability, ensuring alignment with organizational goals. The emphasis on innovation capabilities as a driver of AI adoption further supports these measurement initiatives, aligning with prior studies (e.g., Burström et al. 2021; Chauhan et al. 2022; Xie et al. 2019). By integrating financial oversight mechanisms and standardized metrics, organizations can ensure that AI projects are both effective and aligned with their long-term sustainability objectives.

Finally, this study offers a nuanced understanding of the factors that facilitate AI's integration into corporate sustainability efforts. By synthesizing insights across organizational capabilities, leadership, technical infrastructure, and performance measurement, it offers a comprehensive framework by which to address barriers to AI adoption. These findings bridge critical gaps in the literature and provide actionable strategies for leveraging AI to achieve sustainability goals.

5.2 Managerial contributions

Integrating AI into sustainability efforts necessitates the fostering of an operational culture that embraces innovation and technological advancements. Managers must promote a mindset shift that compels employees to perceive AI not merely as a tool for raising efficiency but as a critical enabler of sustainable practices. Encouraging a culture of ongoing learning and adaptability ensures that the workforce is prepared to leverage AI solutions in pursuit of long-term sustainability goals. Leadership plays a pivotal role in aligning AI initiatives with sustainability objectives. Managers must develop clear, forward-thinking strategies that integrate AI into the organization's broader environmental, social, and governance (ESG) goals. Effective leadership should not only champion AI adoption but also guide the organization through change-management processes, ensuring that AI-driven sustainability becomes a

core element of the company's strategic direction. AI-driven sustainability initiatives require collaboration across multiple stakeholders (both internally and externally) through strategic partnerships. Managers must engage stakeholders in a transparent manner to showcase how AI contributes to their organization's sustainability goals. Building trust through clear communication and collaboration helps to ensure that stakeholders are on board with AI implementation and, in turn, to facilitate a smooth adoption.

For AI to be relevant in sustainability management, its impact must be measurable. Managers should implement systems to track and assess how AI technologies contribute to sustainability outcomes (e.g., energy efficiency, waste reduction, carbon footprint). Data-driven impact measurement empowers managers to make informed decisions, optimize AI applications, and highlight tangible improvements to stakeholders. Notably, the success of any AI-driven sustainability initiative hinges on the organization's technical capacity. Managers must ensure that their teams possess the necessary technical expertise to both implement and maintain AI solutions. Investing in infrastructure, upskilling employees, and fostering collaboration between data scientists and sustainability experts are crucial when it comes to building the technical capacity necessary to fully harness AI in the promotion of sustainability. By focusing on the five aforementioned areas, managers can strategically align AI initiatives with sustainability goals, driving innovation, operational efficiency, and long-term environmental impact. Additionally, overcoming a lack of expertise through strategic partnerships and upskilling, addressing data challenges through collaborative data ecosystems, mitigating high initial costs with scalable pilots, building trust through transparent AI models, leveraging AI for circular economy-related practices, incorporating AI into carbon footprint-monitoring and -reduction efforts, and promoting cross-functional AI adoption in decision-making are practical strategies that may be used to bolster the managerial relevance of AI in sustainability. Real-world examples, such as Walmart's AI-driven energy-management systems (Goswami et al., 2024), Tomra's AI-driven waste-management sensors (Jogarao et al. 2024), and PepsiCo's integration of AI throughout its supply chain (Goswami et al., 2022), illustrate actionable steps companies can take to effectively harness AI for sustainability, providing a roadmap for managers to address specific challenges in AI adoption while driving positive sustainability outcomes.

5.3 Future research and limitations

Three areas for further research are particularly compelling and warrant further investigation. First, one of the primary concerns associated with the rising utilization of AI in decision-making processes is the potential for a loss of human emotional capabilities, including empathy, humanity, and conscientiousness. Management decisions pertaining to sustainability frequently require managers to take these human qualities into account in order to understand the broader social, ethical, and emotional implications of any considered actions. As posited by Cullen-Knox et al. (2017), human emotions exert a pivotal influence on corporate decision-making processes and the subsequent evaluations. The lack of such emotions in AI could lead to decisions that are solely data-driven and fail to consider human or moral aspects that are generally

non-quantifiable. Future research should investigate the potential negative impact of this lack on the corporate decision-making process and, in turn, on sustainability outcomes. Second, as AI technologies have evolved, their energy consumption and carbon footprint have become subjects of significant scrutiny. Van Wynsberghe (2021) drew attention to AI's considerable environmental impact, particularly when it comes to the energy consumption necessitated by the training and operation of complex models. It would be beneficial for future studies to investigate the long-term environmental effects of AI's widespread adoption in the field of sustainability and to ascertain whether its benefits outweigh its environmental costs. These trade-offs must be understood if strategies are to be developed that ensure the maximization of its positive impacts and the minimization of its negative impacts. Third, a company's ownership structure (e.g., private, public, cooperative) can significantly influence the priorities and strategies that organizations adopt when integrating AI into their sustainability efforts. Thus, future research should ascertain the impact of such structural variance on the integration of AI in sustainability efforts in order to determine which ownership types are most conducive to ethical and effective AI use. Such an understanding would enable policymakers and business leaders to establish conditions that facilitate optimal (at least with regard to sustainability) AI utilization.

This study is subject to two principal limitations. First, although our reporting has exclusively focused on capabilities that have received the highest amount of research attention, it remains plausible that these capabilities may not necessarily possess the strongest correlation with performance outcomes. To ascertain which capabilities demonstrate the most robust relationships with performance, future research endeavors (e.g., meta-analyses) should be dedicated to each category of capability. Second, in the interviews, participants may have provided responses that they perceived as socially desirable to the interviewer; moreover, discrepancies in how participants comprehended questions or articulated their responses could have introduced variability into the data. These inconsistencies may not be directly tied to the research question, which can complicate efforts to derive accurate conclusions from the results. This limitation highlights the importance of careful design and interpretation for reducing bias and improving data quality.

6 Conclusion

By prioritizing sustainability, fostering adaptability, and aligning AI initiatives with their organizational objectives, businesses can effectively navigate the complexities associated with integrating AI into their sustainability strategies.

This study detailed AI's role in enabling pilot projects and iterative sustainability scaling, means of developing hybrid metrics that combine environmental and financial performance, the use of eco-friendly IT infrastructure to reduce AI's carbon footprint, and means of overcoming legacy system-related challenges in order to achieve seamless AI adoption in sustainability efforts. Businesses must align their AI strategies with their broader sustainability goals if they are to maintain a competitive advantage and drive progress. The role of AI is only becoming increasingly important in securing technological leadership as industries continue to evolve. Companies

must invest in AI capabilities if they are to remain competitive while addressing their sustainability targets. This study explored the potential of AI to drive organizational change toward greater sustainability, highlighting organizational capabilities, stakeholder management, leadership, and performance measurement as key enabling factors. The integration of such factors provides companies with a comprehensive view of their sustainability efforts, improving their strategic decision-making. AI simplifies complex data, increases accuracy, and automates analysis, making hybrid metrics more actionable through its demonstration of both environmental and economic benefits. As regulations evolve, AI will play an even more vital role in supporting the dynamic and robust reporting of sustainability data.

This research explored the incorporation of AI technology into corporate sustainability initiatives. To address the core inquiry—how organizations approach and employ AI technologies to bolster sustainability and the key factors behind their adoption—the underlying data included both direct and indirect applications of AI to organizational sustainability strategies. The research highlighted five key enablers of AI adoption in corporate sustainability: operational culture, leadership and strategy, stakeholder management, impact measurement, and technical capacity. The empirical insights derived from the analysis point to a model of AI-driven sustainability strategies that highlight strategic actions with a focus on implementing sustainable practices. The results broaden the scope of the literature by examining the primary drivers of, obstacles to, and monitoring methods for AI adoption, offering valuable practical guidance. Moreover, it identifies three promising directions for future research on AI's potential in the promotion of sustainable corporate practices.

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