BENCE PISTRUI – PETRA JENEI

# ORGANIZATIONAL STRATEGIES FOR ETHICAL AND SUSTAINABLE AI IMPLEMENTATION

# SZERVEZETI STRATÉGIÁK AZ ETIKUS ÉS FENNTARTHATÓ MI-BEVEZETÉSHEZ

The rapid diffusion of artificial intelligence (AI) has intensified debate about its dual role as a driver of efficiency and a source of environmental, social, and ethical challenges. These challenges include the growing energy and water demands of data centers, hardware-related emissions and e-waste, data governance risks, workforce concerns, and increasing regulatory pressure. While prior research highlights AI's sustainability potential, less is known about how organizations translate ethical and sustainability principles into concrete implementation strategies. This study examines responsible AI adoption under sustainability constraints, using the Technology-Organization-Environment framework extended with ESG and ethics considerations, and the Triple Bottom Line perspective to interpret outcomes. Empirical insights are based on five semi-structured expert interviews with senior executives, AI specialists, and sustainability professionals across industries and national contexts. The findings show that AI supports efficiency, predictive analytics, and sustainability monitoring, but responsible deployment depends on readiness, data quality, workforce capabilities, and governance structures.

Keywords: **AI governance, Triple Bottom Line (TBL), Technology-Organization-Environment (TOE) framework, digital transformation**

A mesterséges intelligencia (MI) gyors terjedése felerősítette azokat a vitákat, amelyek az MI kettős szerepét vizsgálják: egyrészt a hatékonyság növelésének hajtóerejeként, másrészt környezeti, társadalmi és etikai kihívások forrásaként. Ezek a kihívások magukban foglalják az adatközpontok növekvő energia- és vízigényét, a hardverekhez kapcsolódó kibocsátásokat és az elektronikai hulladékot, az adatirányítási kockázatokat, a munkaerővel kapcsolatos aggályokat, valamint az egyre fokozódó szabályozói nyomást. Bár a korábbi kutatások kiemelik az MI fenntarthatósági potenciálját, kevesebb az ismeret arról, hogy a szervezetek miként ültetik át az etikai és fenntarthatósági elveket konkrét megvalósítási stratégiákká. A tanulmány a felelős MI-alkalmazást vizsgálja fenntarthatósági korlátok mellett, a technológia-szervezet-környezet (Technology-Organization-Environment, TOE) keretrendszer ESG- és etikai szempontokkal kibővített változatának alkalmazásával, míg az eredmények értelmezéséhez a Triple Bottom Line (TBL) megközelítést használja. Az empirikus eredmények öt, félig strukturált szakértői interjún alapulnak, amelyekben felsővezetők, MI-szakértők és fenntarthatósági szakemberek vettek részt különböző iparágakból és nemzeti kontextusokból. Az eredmények azt mutatják, hogy az MI támogatja a működési hatékonyságot, a prediktív analitikát és a fenntarthatósági teljesítmény nyomon követését, ugyanakkor a felelős alkalmazás nagymértékben függ a szervezeti felkészültségtől, az adatok minőségétől, a munkaerő kompetenciáitól és a megfelelő irányítási struktúráktól.

Kulcsszavak: **mesterségesintelligencia-irányítás, hármas értékteremtés elmélete, technológia-szervezet-környezet keretrendszer, digitális transzformáció**

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Examining the dual impact of artificial intelligence on operational efficiency and sustainability has become increasingly important, as the rapid expansion of AI adoption contrasts with its growing resource demands. In operational terms, AI enhances profitability by processing large datasets, automating complex decisions, and improving forecasting accuracy, enabling organizations to operate more efficiently and responsively. At the same time, AI is widely regarded as an enabler of sustainable performance, particularly through data-driven environmental decision-making, energy optimization, environmental risk prediction, and improved resource efficiency (Jorzik et al., 2024; Alzoubi & Mishra, 2024). As a result, AI is often positioned as a technological contributor to the United Nations Sustainable Development Goals and the development of more resilient economic and food systems.

In this study, sustainability is treated as the overarching objective of long-term value creation, interpreted through the Triple Bottom Line dimensions of economic performance, environmental protection, and social well-being. Environmental responsibility refers specifically to AI-related energy use, water consumption, emissions, hardware intensity, and electronic waste. ESG is used as an organizational lens that translates sustainability expectations into governance, reporting, accountability, and stakeholder management practices. Ethics refers to the responsible design and use of AI systems, including transparency, fairness, privacy, accountability, human oversight, and the social consequences of automation. Accordingly, the article examines responsible AI implementation as the process through which firms align technological adoption with ESG expectations, ethical principles, and TBL sustainability outcomes.

This strategic interpretation of digital technologies is also reflected in the management literature. Digitalization and data-driven systems should not be understood merely as operational efficiency tools, but as strategic resources that reshape organizational capabilities, decision-making, and long-term value creation (Varga & Csesznák, 2019). Prior studies further show that digital transformation outcomes depend on whether technologies are strategically embedded and aligned with broader organizational objectives rather than adopted in an ad hoc or technology-driven manner (Bauer & Agárdi, 2020). From this perspective, AI influences not only competitiveness, but also how firms balance economic performance with environmental and social responsibilities.

Despite its sustainability-enabling potential, AI adoption creates a central dilemma. While AI can support environmental optimization and responsible resource management, the technology itself is increasingly resource intensive. Advanced AI systems require substantial computational capacity for both training and inference, while data center infrastructure places pressure on energy and water resources. The production, deployment, and disposal of AI-related hardware, including servers, GPUs, and specialized chips, also generate environmental costs through resource extraction, manufacturing emissions, and electronic waste (Varriale et al., 2026; Litvinets, 2024; Hordieiev et al., 2025). Model selection therefore plays an important role in determining AI's environmental impact, as complex architectures generally consume more energy than simpler analytical or classification models.

These dynamics position AI as both a potential solution to sustainability challenges and a source of new environmental risks. As AI systems scale across industries, their cumulative energy, water, and hardware-related impacts raise concerns about the long-term sustainability of widespread AI deployment. This tension highlights the importance of examining not only what AI can achieve, but also how it is implemented and governed within organizations.

These dynamics position AI as both a potential solution to sustainability challenges and a source of new environmental risks. In line with the discourse on responsible digital transformation, this duality underscores the need for a strategic and governance-oriented examination of AI adoption that extends beyond short-term efficiency gains (Szabó & Csontos, 2021). Accordingly, the present study focuses on how organizations at the strategic and operational levels can implement AI in ways that ethically balance economic performance with environmental and social considerations, addressing the trade-offs inherent in the Triple Bottom Line.

Despite the growing body of research on AI and sustainability, relatively little is known about how organizations translate ethical and sustainability-oriented principles into concrete AI implementation strategies in practice, an issue this paper aims to examine. In light of these complexities, he aim of this study is to examine how organizations translate ethical and sustainability-oriented principles into concrete AI implementation strategies, and how they balance AI's operational benefits with its environmental, social, and governance-related risks.

Based on this aim, the study addresses the following research questions:

*RQ1: How do experts perceive AI's contribution to operational efficiency, competitiveness, and sustainability-related monitoring?*
*RQ2: What internal enablers and barriers shape the ethical and environmentally responsible implementation of AI within organizations?*
*RQ3: How do market expectations and regulatory pressures influence organizational strategies for balancing AI-driven efficiency with environmental and social responsibility?*

## Literature review

This literature review distinguishes between AI's sustainability potential, its sustainability-related risks, and the governance mechanisms needed for responsible implementation. Sustainability is understood through the Triple Bottom Line, covering economic, environmental, and social outcomes, while environmental responsibility refers specifically to AI's ecological effects, such as energy use, emissions, water consumption, hardware demand, and electronic waste. ESG is treated as a managerial and

reporting lens, while AI ethics focuses on transparency, fairness, privacy, accountability, human oversight, and workforce implications. Based on this logic, the review discusses AI as both an enabler and a challenge for sustainability, before introducing the organizational and theoretical frameworks used in the study.

## Impacts of AI

Understanding both the enabling and challenging aspects of AI adoption is essential for examining responsible implementation. AI can improve efficiency, decision-making, innovation, and sustainability monitoring, but it also introduces technological, organizational, environmental, and ethical risks. Therefore, this section reviews AI's dual role as both an enabler of sustainability and a source of sustainability-related challenges.

### *AI as an enabler of sustainability*

Artificial Intelligence serves as a critical enabler of sustainability by strengthening data-driven decision-making, optimizing resource use, and supporting environmentally conscious innovation across sectors. Through its capacity to analyze large volumes of information, anticipate risks, and automate complex processes, AI enhances organizational capabilities to reduce environmental impacts and develop greener production systems (Kupi, 2025). When combined with complementary digital technologies such as the Internet of Things (IoT) and Distributed Ledger Technology (DLT), AI contributes to more efficient monitoring, improved transparency, and the creation of new sustainability-oriented business models (Porkodi et al., 2025).

Evidence from an emerging-economy the agricultural sector illustrates how AI significantly improves information processing, supports production problem-solving, and enables environmentally responsible product innovation. It accounts for more than 80% of the ability to integrate diverse data sources, support complex decision-making, and enhance recycling-related processes, while also driving green product innovation through low-resource raw material selection and recyclable product design (Monsalve-Castro et al., 2025).

Studies in manufacturing, logistics, and supply-chain contexts suggest similar enabling effects. AI-driven strategies outperform traditional digital approaches by not only optimizing energy use and reducing waste but also fostering new solutions for carbon removal and environmental restoration (Rashid et al., 2024). Firms that adopt AI demonstrate greater improvements in environmental performance compared to those relying solely on IoT-based enhancements, emphasizing AI's proactive and predictive contribution to sustainability management (Monroy-Osorio, 2024).

Within local energy community and smart-grid contexts, the integration of AI with IoT (AIoT) further reinforces sustainability goals. In emerging local energy communities, IoT-enabled smart grids facilitate real-time monitoring of energy consumption and generation, allowing prosumers and system operators to manage resources more efficiently (Podrecca et al., 2024). AI enhances this infrastructure by optimizing DLT applications, improving their efficiency, security, and energy performance, and enabling more reliable and transparent citizen-centered energy models. The combination of AI, IoT, and DLT thus supports decentralised energy prosumption and contributes to more resilient, low-carbon energy ecosystems (Bokolo, 2024).

### *AI as a source of sustainability challenges*

Although AI has strong potential to advance sustainability, its implementation within green and sustainable supply chains is constrained by several significant barriers. Many challenges arise from the technological, organizational, and regulatory complexities involved in implementing AI into current operations, especially in resource-limited sectors and developing countries. These limitations reduce the ability of AI to fully support circularity, reduce waste, or optimize environmental outcomes (Baumgartner et al., 2025).

A major concern relates to the environmental cost of AI itself. High computational demands, intensive data processing, and the use of non-renewable energy sources can increase energy consumption and carbon emissions, limiting the net sustainability benefits of AI systems (Luo & Zhang, 2025). Furthermore, the successful integration of AI technologies is strongly dependent on the availability of technical skills, which remains limited, particularly among SMEs (Khan et al., 2024). High initial investment costs, specialized skill requirements, and insufficient training all hinder adoption and expand the capability gap between advanced and emerging economies (Luo & Zhang, 2025).

Data-related issues also constrain AI's effectiveness. High-quality, comprehensive datasets are essential for predictive and optimization models, yet supply chains often lack reliable customer behavior data, historical trends, or standardized information. Variability in data reduces model accuracy and requires firms to deploy more efficient algorithms to compensate (Bokolo, 2024). These challenges are further compounded by the limited adoption of circular economy principles and the scarcity of AI applications focused on end-of-life product management, despite the technology's potential to improve resource recovery and waste reduction (Fu et al., 2024).

Technical and integration-related barriers remain substantial. Organizations in technologically complex and regulated contexts may struggle to align AI solutions with sustainability objectives, manage data quality, meet regulatory requirements, and ensure compatibility with Industry 4.0 systems (Bokolo, 2024). Concerns about data privacy, cybersecurity, and compliance with evolving legal frameworks further slow implementation. Resistance to change also persists, as stakeholders may hesitate to adopt AI due to perceived risks, unclear benefits, or high implementation costs (El Saadani Gazar et al., 2024).

These obstacles are amplified in certain industries, where sector-specific requirements complicate AI deployment. Fields such as healthcare, agriculture, and financial

supply chains face unique challenges related to interoperability, validation standards, regulatory restrictions, infrastructure limitations, and environmental variability. In many cases, limited financial and technical resources restrict organizations' ability to integrate sophisticated technologies effectively (Khan et al., 2024).

Finally, the complexity of green supply chain management poses an additional barrier. Implementing green practices requires substantial process adjustments, and manufacturers often struggle to enhance product sustainability using existing tools. This highlights the need for more targeted research, customized AI solutions, and increased funding to support small and medium enterprises in overcoming governance and data management challenges (Porkodi et al., 2025).

## Company perspectives

This section reviews research and practical insights on the ethical and strategic use of AI, focusing on how organizations balance technological innovation with social, environmental, and economic responsibilities. It provides background for understanding how ethical principles are translated into responsible AI implementation.

### *Ethical, organizational, and sustainability perspectives on AI adoption*

Recent study emphasizes that ethical AI governance is deeply related to comprehensive corporate responsibility frameworks, organizational strategy, and the human implications of automation. The increasing integration of AI and automation requires that organizations implement governance frameworks that combine technical efficiency with stakeholder well-being, environmental sustainability, and ethical practices (Rastogi & Pandita, 2025). Corporate Social Responsibility (CSR) plays a role in this shift, as firms are expected to operate transparently and be accountable to employees, customers, and the communities. Effective CSR strengthens reputation, stakeholder trust, and long-term sustainable performance, reinforcing the need for AI governance mechanisms that reflect ethical practices and social expectations (Gandía et al., 2024).

Environmental sustainability adds another important dimension to ethical governance. With the growing urgency of climate challenges, businesses are transitioning from linear to circular models that prioritise resource efficiency, waste reduction, and system-wide coordination across value chains (Varriale et al., 2026). Circular economy principles require firms not only to minimise negative ecological impacts but also to collaborate with stakeholders to redesign products, materials, and processes. AI governance must therefore ensure that automation and data-driven systems support these goals, enabling responsible resource use, promoting transparency, and preventing technologies from reinforcing unsustainable practices (Gandía et al., 2024).

Automation and AI adoption introduce further governance demands related to technological oversight and organisational alignment. Automation has evolved into a strategic driver of efficiency, quality, and competitive differentiation, supported by advances in machine learning, natural language processing, and robotic process automation (Rashid et al., 2024). While these tools streamline operations and reduce costs, they also heighten the need for governance frameworks that manage risks such as job displacement, dependence on digital tools, and the ethical implications of delegating decisions to intelligent systems. Ensuring responsible automation requires policies that address integration challenges, safeguard data quality, and maintain regulatory compliance, while also preparing organisations to respond to emerging technological capabilities (Gandía et al., 2024).

A human-centered perspective is equally essential in ethical AI governance. Employees' skills, motivation, and professional development directly affect how technologies are adopted and embedded within organisational culture. Governance structures must therefore support continuous learning, skills-matching, and equitable adaptation to changing roles (Di Chiacchio et al., 2026). This includes ensuring that automation enhances rather than diminishes career opportunities, reduces workload-induced stress, and promotes employee engagement instead of eroding it. Aligning managerial and employee perspectives on the value and risks of automation is crucial to supporting workforce resilience, mitigating fears of job loss, and maintaining trust in technology-enabled workplaces (Gandía et al., 2024).

Overall, current research underscores that ethical AI governance is not limited to technical regulation but must integrate CSR principles, environmental objectives, responsible automation practices, and workforce-centred policies. This holistic approach enables organisations to leverage AI strategically while preserving sustainability, accountability, and stakeholder wellbeing (Gandía et al., 2024).

### *Strategic AI implementation*

Strategic AI implementation plays a decisive role in enabling organizations to enhance economic, environmental, and technological sustainability. Across contemporary research, AI is portrayed not merely as an operational tool but as a transformative strategic asset that strengthens resilience, fosters innovation, and supports long-term sustainable development.

From an economic and organizational standpoint, AI improves adaptability, fiscal stability, and value creation. Pietrzak (2025) shows that AI-enabled predictive analytics increase the accuracy of budgeting, forecasting, and cash flow management by providing firms with data-driven insight and decision agility. Customer-oriented applications, such as recommendation platforms and conversational agents, further improve service quality and personalization, supporting revenue stability and customer retention (Jorzik et al., 2024). AI also supports procurement, supplier evaluation, pricing, innovation processes, and ESG data collection, thereby contributing to cost reduction, transparency, and regulatory compliance (Pietrzak, 2025).

Beyond large organizations, strategic AI implementation is also relevant for micro, small, and medium enterprises (MSMEs). Chotisarna and Phuthong (2025) identify a "green cluster" of AI-related technical advancements, including big data analytics, machine learning, deep learning, and digital transformation, which can improve competitiveness and innovation. Evidence from over 16,000 MSMEs shows that AI adoption depends on interactions between internal capabilities and external support, demonstrating that digital transformation requires both organizational readiness and ecosystem collaboration. Big data analytics can also support supply chain coordination and risk management, especially during disruptions (Podrecca et al., 2024). Nonetheless, cost and technical complexity remain significant barriers, highlighting the need for strategic support structures and phased AI integration (Chotisarna & Phuthong, 2025).

At the environmental level, strategic AI implementation is strongly linked to green innovation and improved environmental performance. Xu et al. (2025) suggest that AI-driven technical innovation can enhance corporate environmental sustainability when combined with supportive legislation and responsible governance. At the firm level, integrating AI into environmental initiatives, particularly through IoT-enabled monitoring of energy use, emissions, and waste, helps organizations identify inefficiencies, minimize resource consumption, and reduce environmental impact (Alzoubi & Mishra, 2024). AI-enabled knowledge management further strengthens environmental problem-solving by processing large volumes of sustainability data and supporting data-driven decision-making (Rastogi & Pandita, 2025). Firms with strong absorptive capacity are better able to internalize and apply new environmental knowledge, showing that strategic AI implementation must be coupled with cultural commitment and organizational learning (Xu et al., 2025).

Complementing these insights, Zhang (2025) demonstrates that AI adoption positively influences enterprise-level green innovation by improving resource allocation, optimizing decisions, and enabling more sustainable technological development. This effect appears to persist over time, while mature firms may benefit more due to their accumulated experience, infrastructure, and network ties (Kupi, 2025).

Taken together, current research shows that strategic AI implementation is multidimensional, extending across economic functions, innovation processes, organizational capabilities, and environmental performance. Successful integration requires not only technological tools but also supportive governance structures, absorptive capacity, and alignment with sustainability-oriented objectives. However, while prior studies document both the opportunities and risks of AI, less attention has been paid to how organizations translate ethical and sustainability-oriented principles into concrete implementation strategies. Addressing this gap is essential for understanding how AI can be governed and deployed to support long-term environmental and social sustainability alongside economic performance.

## Theoretical frameworks

This study applies the Technology-Organization-Environment (TOE) framework and the Triple Bottom Line (TBL) perspective. TOE is used to examine the technological, organizational, and external environmental factors that shape AI adoption, while TBL is used to interpret the economic, environmental, and social outcomes of AI implementation. ESG and AI ethics are treated as governance lenses that clarify how organizations manage responsibility, accountability, transparency, and sustainability during AI adoption.

### *Technology-organization-environment*

From a theoretical standpoint, this study extends the traditional Technology-Organization-Environment (TOE) framework by incorporating ESG + Ethics (Environmental, Social, Governance + Ethical) considerations to better explain artificial intelligence (AI) adoption. The TOE framework has been widely used to analyze organizational technology adoption by focusing on technological characteristics, organizational readiness, and environmental pressures (Tornatzky & Fleischer, 1990). However, prior research has noted that TOE primarily emphasizes operational feasibility and efficiency, offering limited insight into the ethical, social, and sustainability implications of advanced digital technologies. (Baker, 2012; Oliveira & Martins, 2011; Senna et al., 2023).

This limitation is particularly evident in the case of AI, which introduces governance challenges related to data privacy, transparency, accountability, and algorithmic bias. Ethical AI research highlights that AI systems function as socio-technical technologies whose impacts extend beyond organizational boundaries and directly affect societal outcomes (Floridi et al., 2018; Jobin et al., 2019). As a result, scholars increasingly argue that traditional technology adoption frameworks require conceptual extension to capture responsible and sustainable AI implementation.

In parallel, research on responsible innovation and corporate sustainability emphasizes the growing importance of environmental, social, and governance considerations in strategic decision-making. Responsible innovation frameworks stress the need to align technological development with ethical acceptability and long-term societal value (Stilgoe et al., 2013; von Schomberg, 2013), while ESG-oriented research demonstrates that sustainability and governance practices significantly influence organizational legitimacy and performance (Eccles et al., 2014; Gillan et al., 2021).

Building on these insights, this study integrates ESG + ETHICS dimensions into the TOE framework to provide a more comprehensive lens for analyzing AI adoption. TOE dimensions capture core adoption capabilities, whereas ESG + ETHICS dimensions explicitly address sustainability objectives, ethical risks, and governance mechanisms shaping AI deployment. This integrated approach is particularly relevant for SMEs and organizations operating in emerging economies, where institutional support and regulatory clarity are often limited, increasing the risks associated with ungoverned AI adoption (Dwivedi et al.,

2021; Kittipanyangam et al., 2025). By linking AI adoption with responsible innovation, the extended TOE + ESG + ETHICS framework enables a holistic assessment of both adoption drivers and sustainability outcomes.

*Triple Bottom Line*

Systems theory provides a foundational perspective for analyzing the Triple Bottom Line (TBL) framework, which integrates economic, environmental, and social dimensions of sustainability. By emphasizing the interconnections among system components, this approach enables a holistic understanding of how these dimensions interact. In particular, systems theory highlights the relationships among subsystems, allowing sustainability outcomes to be examined through feedback loops, trade-offs, and synergies (Kusmendar & Normasari, 2025). Such a systems-oriented lens facilitates informed decision-making in complex sustainability contexts, where interventions in one dimension such as environmental initiatives can produce significant effects on economic and social outcomes.

The TBL framework operationalizes systems thinking by promoting a balanced approach to economic viability, social equity, and environmental protection (Kusmendar & Normasari, 2025). It has been increasingly implemented in corporate sustainability practices as a strategic tool to strengthen organizational resilience, stakeholder accountability, and long-term value creation. From a systems perspective, effective TBL adoption requires continuous learning and adaptive governance to respond to evolving sustainability challenges. Systems-based methods including system dynamics, agent-based modeling, and input-output analysis, have been applied to evaluate the impact of policy interventions on sustainable development, reinforcing TBL's focus on interdependence, feedback processes, and non-linear change dynamics (Kusmendar & Normasari, 2025).

This theoretical foundation underpins the present study's objective to examine how systemic, cross-disciplinary, and digital integration strategies influence TBL implementation across sectors. Moreover, the incorporation of digital technologies into sustainability reporting frameworks, such as the Global Reporting Initiative (GRI), underscores the growing synergy between Industry 4.0 enablers and TBL dimensions, particularly in manufacturing and service industries.

Taken together, the TOE framework extended with ESG + ETHICS dimensions provides a structured lens for analyzing the drivers, enablers, and constraints of AI adoption, while the Triple Bottom Line framework offers an outcome-oriented perspective on the economic, environmental, and social implications of these adoption processes. In this study, TOE + ESG + ETHICS is used to examine how organizations approach AI implementation at strategic and operational levels, whereas TBL is applied to interpret the sustainability trade-offs and performance outcomes associated with these practices. The combined use of these frameworks enables a holistic assessment of both the implementation logic and the sustainability consequences of AI adoption.

## Methodology

The methodology section describes the research design and data collection process applied in this study. It explains how the data were gathered, the criteria used for selecting the interviewees, and the reasoning behind their inclusion. Additionally, it outlines how the interview questions were developed and structured to address the research objectives. As our main methodology, we employed Directed Qualitative Content Analysis. Unlike purely inductive approaches where themes emerge from the data alone, our analysis was primarily driven by the integration of the TOE framework and ESG+E dimensions. This theoretical grounding ensures that the analysis remains aligned with established organizational and sustainability constructs while allowing for nuanced insights from expert participants. Consequently, deductive coding was based on the pre-defined elements of the TOE framework and ESG+E dimensions (Kibiswa, 2019).

### Data collection type

This study is rooted in the interpretivist paradigm, which seeks to understand organizational realities through the subjective experiences of experts (Alharahsheh & Pius, 2020). Therefore a semi-structured interview is a highly effective research method because it balances consistency with flexibility, making it particularly valuable for exploring complex or emerging topics such as AI and sustainability. This approach ensures that all participants address comparable core issues, improving reliability, while still capturing rich, nuanced insights that reflect their unique experiences, expertise, and perspectives (Kvale & Brinkmann, 2015). It is especially suitable when the aim is to understand not only what people think but why they think it, enabling the researcher to uncover underlying motivations, contextual factors, and previously unanticipated challenges or opportunities.

In management and organizational research, semi-structured interviews are widely applied in exploratory studies where the objective is to examine strategic decision-making, technology adoption, and organizational practices in contexts characterized by uncertainty and complexity (Saunders et al., 2019). As a result, this method supports a more holistic and grounded understanding of organizational realities, making it particularly appropriate for qualitative studies examining AI adoption, internal capabilities, and sustainability-related decision-making processes.

### Data collection process

The data gathering method for this research commenced with a focused LinkedIn search to discover AI specialists possessing relevant experience and knowledge in this field. Participants were identified through a focused LinkedIn search and selected through purposive sampling. LinkedIn was used as an access point rather than as the sole basis for determining expertise. Suitability was assessed based on publicly available professional information, including senior or expert-level roles (Chief Sustainability Officer, Chief Data Officer, and AI Executive Leaders*)*, direct experience with AI, data, sustainability, ESG, or governance, and

evidence of involvement in organizational or sector-level AI implementation. The sample was also designed to include geographic and sectoral diversity (e.g., UAE, UK, Spain, Finland, the EU AI Act versus the UAE AI Chapter*)*, allowing the study to capture perspectives from different regulatory and market contexts. Upon collecting an initial list of potential specialists, we started communication via LinkedIn messages explaining the research's objective and offering an invitation for their participation. Upon receiving positive responses, we arranged virtual meetings with Microsoft Teams, providing an accessible setting for synchronous discussions. In these meetings, we engaged in thorough discussions, obtaining significant insights regarding the experts' experiences with AI implementation and its effects on sustainability. Following to the sessions, we transcribed the discussions in order to document essential points and details, which subsequently formed the basis for analysis in the later stages of the research. This procedure facilitated a systematic and effective method for collecting expert insights, enabling a thorough comprehension of AI's function in sustainability practices.

## Interview profile

The interviewees for this research included a diverse group of experts, each bringing a unique perspective on AI, sustainability, and ESG (Environmental, Social, and Governance) practices. Participants were selected to ensure representation from different regions, markets, and professional environments in order to capture a broad range of insights on the topic. Additionally, all interviewees were chosen based on their demonstrated expertise, either through relevant academic research or substantial professional experience related to AI implementation, governance, or sustainability. This selection approach helped ensure that the findings reflect informed perspectives from experts with direct knowledge of the field. (Table 1).

## Interview questions

To structure the development of the interview questions, this study combined the Technology-Organization-Environment (TOE) framework with the Triple Bottom Line (TBL) sustainability model. The TOE framework was used to capture the technological, organizational, and external environmental factors influencing AI adoption, while the TBL framework provided the sustainability perspective by considering social, economic, and environmental impacts. As illustrated in Figure 1, the TOE dimensions were positioned along the vertical axis and the TBL dimensions along the horizontal axis, creating a matrix that guided both the design of the interview questions and the subsequent analysis. This structure allowed the study to systematically explore how different drivers of AI adoption interact with sustainability outcomes.

Figure 1

**Combined Framework**

| | TOE modell/ Sustainability | Social | Economic | Environment |
|---|---|---|---|---|
| Technological | AI relative advantage | | | |
| | AI readiness | | | |
| Organisational | Employee readiness | | | |
| | Support activities within organisation (eg. financing) | | | |
| | Main activities within organisation (eg. customer experience, manufacturing) | | | |
| Business External Environment | Market opportunities | | | |
| | Competitive pressure | | | |
| | Customer needs | | | |
| | Government involvement (support/barrier) | | | |

*Source: own editing*

Table 1

**Interview Profiles**

| Interview | Country | Position | Description |
|---|---|---|---|
| I.1 | UAE | Chief Sustainability Officer | His insights are grounded in extensive corporate sustainability experience, leadership roles, and expertise in integrating ESG strategies into organizational frameworks. |
| I.2 | Finland | Researcher | He specializes in advanced technologies relevant to corporate strategy. His academic background provides a strong theoretical foundation, and his research focuses on emerging technologies, including the strategic application of artificial intelligence in business sustainability. |
| I.3 | UK | Chief Data Officer | With deep expertise in data management and artificial intelligence, he works on leveraging data-driven insights to optimize business performance and sustainability initiatives, positioning him at the intersection of technology, data, and sustainability. |
| I.4 | Spain | AI expert, executive leader, and chair of the board of directors | Drawing on substantial experience in the healthcare sector, his expertise centers on applying AI technologies to improve operational efficiency and support sustainable practices, particularly in healthcare-related industries. |
| I.5 | UK | AI expert specializing in sustainability | His work focuses on the use of artificial intelligence to advance sustainability objectives, examining how AI-based solutions can reduce environmental impacts and foster sustainable business innovation. |

*Source: own editing*

Based on this framework, the interview questions (see Appendix 1) were grouped into three main areas corresponding to the TOE dimensions. First, technological aspects focused on the perceived relative advantage of AI and the technological readiness of organizations, including considerations related to efficiency, employee impact, and environmental implications such as energy consumption. Second, organizational factors addressed internal readiness for AI adoption, including employee preparedness, financial and operational support functions, and the integration of AI into core organizational activities. Third, external environmental factors examined the influence of market opportunities, competitive pressure, customer expectations, and government involvement on the responsible and sustainable implementation of AI. By structuring the interviews along these dimensions, the study ensured that each sustainability aspect of the TBL model could be examined in relation to the key drivers of AI adoption identified in the TOE framework.

## Results

We have organized the Results section based on the logic of the TOE model as it applies to AI, detailing each part through the lens of ESG+E considerations.

### Technological - perceived advantages and readiness

This subsection addresses RQ1 by analyzing experts' perceptions of AI's contribution to operational efficiency, competitiveness, and sustainability-related monitoring.

The interviews with AI experts revealed a multifaceted understanding of AI's perceived advantages and organizational readiness, highlighting both its promise and current limitations in sustainability and business contexts. Across the discussions, AI's role in operational efficiency, predictive analytics, environmental monitoring, employee support, and compliance emerged as recurring themes, although its impact varied depending on sector, organizational maturity, and regulatory context.

Several experts emphasized AI's capacity to improve operational performance and environmental efficiency. I.1 noted that predictive analytics are particularly valuable in energy-intensive industries, such as oil and gas, where demand forecasting and resource allocation are critical. AI can improve productivity, reduce costs, optimize resource use, minimize downtime, and support real-time monitoring of critical systems. This allows organizations to detect anomalies and intervene proactively, which is especially relevant for environmental management and compliance. I.1 also highlighted AI's role in climate action, including emission tracking and renewable energy optimization, contributing to a more sustainable energy mix.

I.3 similarly acknowledged AI's potential to improve environmental efficiency through initiatives such as smart energy monitoring systems, but noted that implementation often lags behind ambition, with projects only partially deployed and operationalization still limited. I.4 added that, in the commercial sector, AI applications are usually focused more on personalization and efficiency than direct environmental impact, although such technologies may still support more sustainable consumer decision-making.

Experts also consistently recognized AI's potential to enhance business performance. I.4 explained that adoption differs across sectors: startups and AI-native companies tend to show higher maturity, while traditional organizations are still integrating AI to improve customer experience and product performance. Examples include AI-driven customer support in financial services and personalized health-tech messaging to influence behavior change. I.5 added that AI can simplify complex sustainability compliance tasks by making regulatory knowledge more accessible, although regulatory acceptance remains a constraint. I.2 similarly highlighted AI's ability to automate tasks and generate insights, such as sentiment analysis from meeting transcripts, thereby improving oversight and decision-making.

AI's impact on employee well-being emerged as both a benefit and a challenge. I.1 and I.3 emphasized AI's potential to de-skill routine tasks and allow employees to focus on higher-value work. However, I.3 noted that tangible benefits for employee well-being remain limited, as many initiatives are still early-stage and their return on investment is difficult to measure. I.4 highlighted employee anxiety around job displacement, especially among lower-skilled workers, while I.2 stressed the importance of localized AI models to ensure accurate and culturally appropriate insights that support employees rather than produce skewed outcomes.

Organizational readiness varied considerably. I.5 described high preparedness through the integration of AI tools across operations, investment in training and expertise, and the appointment of senior AI leadership. In contrast, I.2 and I.3 noted that many organizations remain at an early stage, struggling to align AI with existing systems and strategies. Common barriers include immature technologies, limited financial and technical resources, difficulties in measuring ROI, and regulatory compliance requirements. As I.2 and I.5 emphasized, audit requirements such as the ESOS framework cannot always be met through AI-generated data, limiting AI's use in legally binding sustainability reporting.

In summary, AI is perceived as a transformative force for both operational and environmental efficiency, mainly through predictive analytics, automation, real-time monitoring, and data consolidation. However, its benefits depend strongly on organizational readiness, sector-specific maturity, data quality, regulatory acceptance, and strategic alignment. The findings also reveal a psychological duality for employees: AI can improve productivity and reduce routine work, but it may also increase job insecurity and anxiety. Overall, AI's advantages are significant, but they remain highly context-dependent and require careful governance, training, and change management.

### Organisational - the internal enablers and barriers

This subsection addresses RQ2 by examining the internal financial, technical, organizational, and workforce-related enablers and barriers that influence ethical and environmentally responsible AI implementation.

The interviews revealed a complex interplay of internal enablers and barriers affecting AI adoption. Financial, technical, and human-resource capabilities emerged as key enablers, while cost, data quality, organizational culture, and workforce readiness were repeatedly identified as major obstacles.

Financial readiness was both an enabler and a constraint. I.1 reported that AI had already been integrated across 60-70% of critical operational areas, showing strong commitment to adoption, but also emphasized that implementation costs remain substantial and can be especially prohibitive in developing regions. I.4 noted that while some companies can finance AI experimentation, few have the resources to develop proprietary models and therefore rely on pre-built or open-source solutions. Similarly, I.5 highlighted that smaller organizations often struggle to invest in AI infrastructure and expert personnel, although internal resources can help reduce development costs. I.2 added that many organizations still lack the investment capacity required for infrastructure and tailored AI models.

Technical readiness also functioned as both an enabler and a barrier. I.1 pointed to data synchronization challenges, particularly when integrating AI with legacy systems such as Enterprise Resource Management platforms, which can create inefficiencies and delays. I.5 stressed the importance of high-quality, well-structured data, as incomplete or inconsistent datasets compromise AI outputs and increase the risk of hallucinations or misleading results. I.2 further emphasized the need for culturally and contextually tailored AI models, since generic systems may produce inaccurate insights in specific organizational or regional contexts.

Employee readiness was another key determinant of successful adoption. I.1 described hands-on training programs and a largely IT-literate workforce, but also noted resistance among shop-floor employees concerned about job displacement. I.4 observed that employees are increasingly learning to use tools such as large language models, although adoption often remains ad hoc and lacks coordinated strategies or ethical frameworks. I.2 emphasized the need for reskilling, upskilling, and AI literacy across organizational levels as traditional roles evolve. I.3 reported similar challenges in academic settings, where professional staff showed more resistance than technically skilled researchers, and training initiatives remained largely voluntary and unstructured.

Organizational culture and structure further shaped AI integration. I.5 noted that smaller, agile startups often adopt AI more quickly, while larger, bureaucratic organizations face slower progress due to internal complexity, policies, and experimental integration approaches. I.4 stressed that many organizations are still learning how to implement AI strategically and ethically, while I.2 described a "submerged iceberg" phenomenon, where organizations understand surface-level AI capabilities but remain unaware of deeper, transformative applications.

The empirical data also validated the sustainability paradox of AI. I.4 illustrated this through the "Stargate" project in Texas, a large-scale data center initiative by OpenAI and its partners, projected to require approximately 15 terawatts of energy capacity, comparable to the energy consumption of major global cities such as New York, Paris, or Tokyo. This suggests that AI infrastructure is not only a business asset but also a global resource competitor. I.1 added that the issue extends beyond electricity, as HVAC and refrigeration systems for large data processing units create significant water footprints, a critical bottleneck often overlooked in sustainability discussions.

In summary, internal AI integration is enabled by financial investment, technical infrastructure, high-quality data, internal expertise, and employee training. However, it is hindered by high implementation costs, legacy-system integration, poor data quality, AI hallucinations, limited strategic expertise, and workforce resistance. Human capital readiness depends on structured upskilling, while sustainability concerns show that AI adoption must be assessed not only as a technological or business decision, but also as a resource-intensive environmental challenge.

### Business external environment - responding to market and regulatory pressures

This subsection addresses RQ3 by exploring how market expectations, competitive pressure, customer needs, and regulatory frameworks shape organizational strategies for balancing AI-driven efficiency with environmental and social responsibility.

The interviews show that organizations are increasingly pressured by market expectations and regulatory frameworks to adopt AI, with direct implications for competitiveness, operational efficiency, and sustainability. Across sectors, AI is no longer perceived as optional, but as a strategic necessity in an evolving business environment.

Experts consistently identified market demand as a key driver. I.1 noted that both business-to-business (B2B) and business-to-consumer (B2C) customers increasingly expect AI-driven solutions. Organizations that fail to adopt AI risk losing competitive advantage, as AI enables innovation, efficiency, and improved products and services. I.4 similarly highlighted AI's role in personalization, efficiency, and identifying emerging market gaps, while stressing that human decision-making remains essential for acting on these insights. I.5 discussed AI's value in sales, marketing, and customer engagement, especially in smaller-scale applications, but noted that larger, regulated sectors adopt AI more slowly due to compliance and traceability requirements. I.2 added that tools such as Generative Engine Optimization (GEO) are transforming digital marketing by requiring firms to optimize not only for human consumers but also for AI systems that increasingly influence customer traffic. I.3

emphasized that although higher education institutions recognize AI's potential for efficiency and competitiveness, adoption remains early-stage, with processes and roles still evolving.

Regulatory pressures act as both enablers and barriers. I.1 observed that while regions such as the EU have developed AI regulations, many countries, including emerging economies, still lack robust AI frameworks, creating challenges for ethical adoption and data governance. I.4 and I.5 similarly noted that inconsistent or underdeveloped regulation creates uncertainty, while governmental financial support remains limited. I.2 and I.3 described the EU AI Act as an important milestone in human-centric AI governance, but warned that overly restrictive regulation could slow innovation and discourage foreign direct investment. Across interviews, data privacy, traceability, and auditability were repeatedly identified as critical compliance concerns, especially in regulated sectors.

Although some governmental incentives exist, experts agreed that organizations often need to self-fund AI adoption. I.1 and I.4 emphasized the importance of prioritizing AI deployment in high-impact areas under budget constraints. I.5 highlighted localized, site-specific AI solutions as more manageable and cost-effective sustainability interventions than large centralized projects. I.2 added that although AI's initial energy consumption is high, its long-term application may generate sustainability efficiencies, aligning with the Kuznets curve logic, where technological maturity eventually reduces environmental impact.

In summary, market and regulatory pressures jointly shape AI adoption. Market demand encourages innovation, efficiency, personalization, and customer engagement, while regulation defines the boundaries for ethical, accountable, and legally compliant AI use. However, successful adoption depends on balancing competitiveness, compliance, technological capability, workforce readiness, financial investment, data quality, and targeted deployment. The findings suggest that AI's sustainability potential is strongest when organizations use it strategically in high-value areas while managing its regulatory, ethical, and environmental constraints.

## Managerial implications

For managers, the discussion highlights that AI should not be viewed solely as a tool for boosting operational efficiency but as a technology with significant sustainability trade-offs. While AI can optimize energy use, improve forecasting, and enhance decision-making, it simultaneously increases energy consumption, water usage, and hardware-related emissions. Managers must therefore adopt a dual approach: capturing the performance benefits of AI while actively mitigating its environmental footprint. This requires evaluating the lifecycle impact of AI systems, choosing appropriately scaled models, and integrating renewable energy and efficient data-center solutions into digital strategies.

The text underscores that successful AI adoption depends not just on technology, but on organizational readiness, workforce capability, and ethical governance. Managers must prioritize skill development, cross-functional collaboration, and transparent governance frameworks to ensure responsible and sustainable AI use. This includes aligning AI initiatives with Corporate Social Responsibility, establishing policies for data quality, privacy, and fairness, and ensuring employees are supported through reskilling and change-management processes. Doing so helps managers avoid resistance, reduce implementation risks, and improve stakeholder trust.

Managers can leverage insights from the literature to understand that AI becomes most valuable when strategically deployed to support broader organizational and sustainability objectives, rather than being adopted opportunistically. AI can strengthen green innovation, improve ESG reporting, enhance supply-chain transparency, and support circular-economy initiatives. By integrating AI within sustainability strategies through predictive monitoring, smart resource management, and data-driven environmental decision-making, managers can enhance long-term resilience and contribute to the Triple Bottom Line. This positions the company not only for economic benefits, but also for improved environmental and social performance.

To address the long-term environmental viability of AI, this study proposes the application of the Environmental Kuznets Curve (EKC) theory to digital transformation. According to Expert I.4, AI is currently at the beginning of the industrialization slope, where its negative environmental impact is at its peak due to high energy and resource consumption. However, the model suggests that as AI technology matures and reaches a high level of integration, it will identify systemic efficiencies that reverse the curve, eventually leading to net-positive environmental outcomes. For decision makers, this implies that the focus should not be on halting AI adoption due to its initial footprint, but on accelerating the transition through the curve by incentivizing 'Green AI' architectures and mandatory resource disclosure. This perspective transforms the sustainability challenge from a static 'energy problem' into a dynamic 'efficiency transition'

## Theoretical implications

This study offers significant theoretical value by deepening academic understanding of the dual role of Artificial Intelligence in organizational efficiency and sustainability performance. By synthesizing evidence on AI's ability to enhance predictive analytics, resource optimization, and environmental monitoring, the text advances theoretical discourse on how digital technologies function as socio-technical systems rather than purely operational tools. For researchers, this duality highlights the need to conceptualize AI not only as an enabler of sustainability but also as a generator of new ecological pressures due to its energy, water, and hardware demands. This creates an important theoretical tension that invites further investigation into the trade-offs, systemic feedback loops, and boundary conditions that determine when AI produces net-positive sustainability outcomes.

Furthermore, the text contributes to theoretical frameworks that examine technology adoption, particularly the TOE and Triple Bottom Line models. By integrating these models with ethical and ESG considerations, the analysis extends traditional theoretical boundaries and encourages scholars to adopt a more holistic lens when assessing digital transformation. The work suggests that AI adoption cannot be fully explained by technological readiness alone; instead, it requires a multidimensional understanding of governance, social responsibility, circularity, and organizational learning. This expanded theoretical framing supports the development of more robust models that capture the interplay between digital innovation, sustainability strategies, and organizational capability building.

Finally, the text enriches academic discussions on responsible AI governance by linking AI-driven transformation with emerging sustainability demands and human-centered organizational dynamics. Researchers studying ethical AI, sustainability transitions, or organizational adaptation can draw on these insights to develop new theories about how firms navigate technological ambiguity, regulatory constraints, and societal expectations. By positioning AI at the intersection of economic performance, environmental stewardship, and employee well-being, the text provides a comprehensive foundation for future theoretical work exploring how advanced technologies shape systemic sustainability outcomes across industries and contexts.

## Limitations of research

This study has several limitations. First, the empirical scope is narrow, as the findings are based on semi-structured interviews with a small group of experts. Although participants had relevant experience in AI, sustainability, and ESG governance, their views cannot be generalized across all industries, regions, or organizational maturity levels. A further limitation concerns the use of LinkedIn as the primary channel for identifying interviewees. Although participants were screened based on professional experience, expertise, and relevance to the research topic, LinkedIn-based recruitment may still introduce selection bias. It may favor more visible professionals, individuals active on the platform, or those whose expertise is more explicitly presented in public profiles.

Second, AI technologies and sustainability regulations are evolving rapidly. Therefore, the findings represent a specific moment in time and may change as AI systems become more efficient, regulatory frameworks mature, and organizational governance practices develop.

Third, the study relies partly on expert perceptions rather than measured environmental or operational data. Many organizations still lack complete information on AI-related energy use, resource consumption, ROI, or employee outcomes. Future research should therefore incorporate quantitative environmental metrics, longitudinal data, and additional organizational variables such as workforce demographics, digital maturity, and sector-specific adoption patterns.

## Summary

Artificial Intelligence plays a dual role in contemporary organizations, acting as both a powerful enabler of sustainability and a source of new environmental pressures. On one hand, AI enhances operational efficiency, predictive analytics, and resource optimization, enabling firms to reduce energy consumption, minimize waste, and support resilient systems aligned with the Sustainable Development Goals. Its integration with complementary technologies such as the Internet of Things and Distributed Ledger Technology further strengthens data-driven decision-making, promotes green innovation, and supports decentralized, low-carbon energy systems.

However, AI adoption is not without challenges. Technology itself consumes significant energy, relies on resource-intensive hardware, and contributes to water use and electronic waste, creating a sustainability paradox. The interviews with AI experts highlighted that these environmental costs, combined with high implementation complexity, workforce readiness issues, and regulatory constraints, often limit the net sustainability benefits of AI. Experts noted that while AI improves operational performance and ESG reporting, tangible benefits for employee well-being and environmental outcomes are highly dependent on organizational maturity, sector context, and targeted deployment strategies.

Interviewees emphasized several internal and external enablers for effective AI adoption. Financial and technical readiness, high-quality data, and employee training emerged as key internal factors, while market demand and regulatory pressures acted as external drivers. Conversely, barriers such as high costs, workforce resistance, data limitations, and inconsistent regulations hinder AI integration. Strategic implementation, coupled with ethical governance, organizational learning, and alignment with sustainability objectives, was repeatedly identified as crucial to unlocking AI's full potential for the Triple Bottom Line: economic, environmental, and social performance.

Overall, AI presents a complex trade-off: it is a transformative tool that can advance sustainable business practices, yet its deployment requires careful management of environmental and social impacts. Organizations that adopt AI strategically, integrate supportive governance frameworks, and prioritize workforce readiness are best positioned to leverage its benefits while mitigating potential negative consequences. The study underscores the need for ongoing research into context-specific strategies, policy frameworks, and measurement approaches to ensure AI contribute positively to long-term sustainability.

During the preparation of this work the author(s) used [ChatGpt and Quillbot] in order to [Citation check, fluency, and guideline check]. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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## Appendices

### Appendix 1 Interview questions

1. Based on your experience, how has the introduction of AI technologies changed organizational operations in terms of employee well-being and inclusion, business performance and competitiveness, and environmental efficiency or sustainability?
2. Based on your experience, in what ways are organizations technologically and financially prepared to adopt AI responsibly, while ensuring employee readiness, sustainable investment, and consideration of environmental impacts such as energy use or e-waste?
3. Based on your experience, how do organizations prepare and support employees for AI-driven change, for example socially through trust and inclusion, economically through skill development and productivity gains, and environmentally through awareness of sustainable technology use?
4. Based on your experience, how do internal support functions such as HR, IT, or finance enable the ethical, financially responsible, and environmentally conscious integration of AI across organizations?
5. Based on your experience, how is AI integrated into organizations' main activities in ways that enhance customer relationships and social value, improve operational and economic performance, and contribute to environmental goals such as efficiency or waste reduction?
6. Based on your experience, how do AI-driven market trends create opportunities for organizations to promote social inclusion, generate sustainable economic growth, and develop environmentally friendly products or services?
7. Based on your experience, how does competition influence organizations' approach to AI adoption in terms of social responsibility, economic resilience, and environmental performance?
8. Based on your experience, how are evolving customer expectations around ethics, affordability, and environmental responsibility shaping the way organizations design and deliver AI-enabled products or services?
9. Based on your experience, how do government policies, incentives, or regulations affect organizations' ability to implement AI in a socially responsible, economically sustainable, and environmentally conscious manner?