Routledge
Taylor & Francis Group

Industry and Innovation

ISSN: 1366-2716 (Print) 1469-8390 (Online) Journal homepage: www.tandfonline.com/journals/ciai20

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To cite this article: René Bohnsack, Jonatan Pinkse & Georg Reischauer (2026) Artificial Intelligence and the twin transition: the good, the bad, and the ugly, Industry and Innovation, 33:7, 806-825, DOI: 10.1080/13662716.2026.2683371

To link to this article: https://doi.org/10.1080/13662716.2026.2683371

INDUSTRY AND INNOVATION
2026, VOL. 33, NO. 7, 806–825
https://doi.org/10.1080/13662716.2026.2683371

Artificial Intelligence and the twin transition: the good, the bad, and the ugly

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ABSTRACT

Artificial Intelligence (AI) is the critical test case for the twin transition, the interplay of the digital and the green transformation, as it can reduce but also increase negative environmental effects. By synthesising recent advances, this paper develops an integrative firm-level understanding of AI's role in the twin transition. First, we propose a typology of effects through which AI shapes environmental outcomes: efficiency and footprint effects, prebound and rebound effects, and unlocking and path-escalating effects. Second, we show that these effects are not properties of AI itself but emerge from how firms choose to manage interactions between effects strategically. To nuance the interplay of effects and strategic choices, we develop and illustrate three AI adoption configurations: sustainability-amplifying, productivity-stabilising, and harm-amplifying AI adoption. Our paper offers new research avenues on AI and environmental sustainability as well as actionable guidance for managers and policymakers seeking to steer AI deployment towards sustainable effects.

KEYWORDS

ecological sustainability; Artificial Intelligence; generative AI; digital innovation; environmental sustainability; twin transition; Digital Sustainability

JEL CLASSIFICATION

O14; O33; Q55; Q56

The key to unlocking a net-zero future [. . .] is transforming the way industrial teams work through digitalization.

Peter Herweck , CEO Schneider Electric

1. Introduction

In recent years, two major transitions – green and digital – have co-evolved and now jointly drive innovation in multiple industries. Riding the momentum of these transitions, the pace of innovation has accelerated, also in traditionally slow-moving industries such as electricity generation, automotive production, and manufacturing. Across sectors, industrial innovations now increasingly integrate digital and green technologies. For example, artificial intelligence (AI) and digital twins facilitate renewable-energy integration into smart grids, the optimisation of electric-vehicle charging and energy consumption of buildings, and more effective predictive maintenance and process optimisation to reduce energy and material waste. This phenomenon is commonly referred to as the twin transition (Calvino, Dechezleprêtre, and Haerle 2025,; Diodato et al. 2023; Faggian, Marzucchi, and Montresor 2024), broadly defined as the parallel shifts towards digitalisation and environmental sustainability.

The twin transition assumes complementarity between green and digital transitions. Progress towards a more sustainable economy increasingly depends on digital technologies to manage complexity, especially AI, which many see as a highly impactful general purpose technology with strong innovation potential (Holm et al. 2023). Under mounting regulatory pressure to curb greenhouse gas emissions and mitigate environmental degradation, incumbents must reimagine core products and services without relying on fossil fuels, especially in emission-intensive industries such as energy, mobility, and manufacturing (Pinkse, Demirel, and Marino 2024). This challenge is systemic rather than incremental: it demands reconfiguring how energy is produced, mobility is organised, and materials are sourced and processed. AI has emerged as a critical enabler by offering tools that manage complexity, enhance efficiency, and accelerate innovation

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(George, Merrill, and Schillebeeckx 2021; Kocoglu and Mithani 2026; Perri and Rocha 2024). For instance, balancing the grid at scale amid growing distributed electricity generation from solar and wind, alongside the integration of electric vehicles, would be virtually impossible without extensive AI adoption.

However, tensions also arise between the two transitions. While digital innovation seems indispensable, the rapid rise of AI – illustrated vividly by the widespread adoption of Generative AI tools such as ChatGPT – has profoundly reshaped the discourse on how we think about the connection between green and digital transitions. Clearly, AI has negative environmental effects due to its substantial energy consumption, water use, material extraction, and e-waste generated by data centres and digital infrastructures (Luccioni, Strubell, and Crawford 2025; Lyu et al. 2025). Moreover, many of the anticipated positive effects have not yet materialised at scale and remain largely aspirational. Two effects are particularly concerning: rebound effects, where efficiency gains stimulate consumption that offsets environmental benefits, and path-escalating effects, where AI creates new categories of environmental harm (Luccioni, Strubell, and Crawford 2025). It remains unclear whether AI will accelerate the green transition or whether the prevailing twin transition narrative mainly serves to legitimise AI's expansion while diverting attention from the environmental harms linked to its deployment (Bohnsack, Bidmon, and Pinkse 2022).

In this paper, we move beyond the frequently debated question of whether AI is 'good' or 'bad' for the natural environment and green innovation. Instead, we assume that AI will produce both benefits and challenges, and that firms using AI to become environmentally sustainable must develop a nuanced understanding of these effects. To build this understanding, we first take stock of recent advances on the link between environmental sustainability and AI (Section 1). We then propose a typology that maps AI's environmental effects and specifies how AI enables or undermines firms' twin transition initiatives. We identify six effects – *direct (efficiency and footprint effects), indirect (prebound and rebound effects)*, and *generative (unlocking and path-escalating effects)* – each with distinct implications for environmental sustainability (Section 2). After that, we show that AI adoption does not automatically produce these effects; instead, they depend on firms' strategic choices about the scale and scope of adoption and how tensions between positive and negative impacts are managed. We illustrate this through three AI adoption configurations – *sustainability-amplifying, productivity-stabilising*, and *harm-amplifying* – which detail how AI adoption can produce very different environmental impacts across firms. For each configuration, we describe the firm's strategic context, the strategic objective of adopting AI, the firm's strategic context, dominant AI effects, strategic initiatives, and guardrails that steer AI towards producing environmental benefits and away from unintended trade-offs (Section 3).

Integrating insights from the literature on environmental sustainability and digital innovation, this paper advances our understanding of AI's multifaceted role in the twin transition at the firm level (Section 4). It also provides managers with actionable guidance on how to harness AI's transformative potential while mitigating its environmental impacts. For policymakers, it offers indicators to assess the extent to which, and the conditions under which, firms can steer AI deployment towards environmentally sustainable effects (Section 5).

2. The relationship between AI and environmental sustainability

While innovation research on AI has emphasised its economic and innovation potential (Gama and Magistretti 2025), recent debates highlight a growing interconnection between AI and environmental sustainability (Bohnsack, Bidmon, and Pinkse 2022; Ding et al. 2024; Reischauer and Fuenfschilling 2023). In what follows, we briefly outline key aspects of AI, environmental sustainability, and their relationship.

AI 'is on a positive trajectory towards being considered a genuine GPT [General Purpose Technology]' (Holm et al. 2023, 1147). It spans multiple domains, ranging from discriminative AI (e.g. classification, forecasting, optimisation) to generative AI (e.g. text, images, video, code) and foundation models, which serve as general-purpose infrastructures for creativity, coordination, and complex task execution (Holm et al. 2023). The turn to AI as a pivotal lever for environmental sustainability is based on its potential to increase efficiency and effectiveness (Pinkse and Bohnsack 2021; Spanjol et al. 2024). Efficiency gains arise from automation, optimisation, and accelerated decision support (Raisch and Krakowski 2021). By enabling firms to execute typical environmental management tasks more swiftly, AI makes it more efficient for them to comply with environmental regulations. Effectiveness gains stem from enhanced prediction accuracy, adaptive problem-solving, and the creation of novel digital functionalities. Activities once deemed unattainable, such as measuring environmental effects across remote supply chains, are now increasingly within reach. Specifically, AI's potential arises from at least three affordances. First, AI enhances how firms adapt and learn: models improve through exposure to data and enable tasks such as pattern recognition, prediction, and content generation without explicit reprogramming (Bohnsack, Kurtz, and Hanelt 2021; Nishant, Kennedy, and Corbett 2020). Second, AI systems rely on large-scale data infrastructures and advanced computing power, which broaden the scope of standardised data and allow digital products to perform increasingly complex functions. For example, agricultural supply chains can be made more resilient to extreme weather events by deploying sensors (physical component) that continuously monitor weather conditions and environmental effects, with the resulting data processed through AI systems (digital component) to enable more efficient crop yield management (Effah et al. 2024). Third, generative and agentic forms of AI add a self-augmenting dimension; new outputs, such as text, images, code, and decisions, become inputs for further training, thereby accelerating diffusion (Holldack, Banh, and Strobel 2026).

These AI-specific affordances hold great promise for *environmental sustainability*, which is commonly defined in terms of a firm's ecological footprint, meaning the reduction of harm inflicted on the natural environment, often by means of green or ecological innovation (Perri and Rocha 2024; Reischauer et al., 2025). A key goal for firms following this classic approach to environmental sustainability is achieving a state of neutrality in which the negative environmental effects of a firm are eliminated (Pinkse, Demirel, and Marino 2024). This reductive approach emphasises 'doing less bad' (Borland et al. 2016). Innovation to meet this goal has focused on measuring environmental effects, setting targets, implementing green technologies, monitoring performance improvements, and taking corrective actions. This process depends on collecting, monitoring, and analysing data to inform decision-making. AI significantly enhances this process by expanding its scope and improving efficiency through advanced data collection, real-time analytics, and prediction (Pinkse and Bohnsack 2024). As we detail later, a rapidly growing body of research demonstrates that AI can indeed improve resource efficiency and reduce pollution (Kulkov et al. 2024).

In parallel, scholars have argued that reducing a firm's ecological footprint alone is insufficient to address escalating environmental challenges and have highlighted the need for producing positive effects as well. This regenerative approach to environmental sustainability urges firms to create positive ecological effects instead of lowering their footprints only (Hahn and Tampe 2020; Slawinski et al. 2021). Firms adopting this approach innovate to 'do more good' rather than merely 'do less bad.' However, extending firms' responsibility beyond reducing harm to actively creating positive environmental effects outside their organisational boundaries substantially increases the complexity of managing sustainability and elevates expectations regarding the role of firms. For example, Alipay's Ant Forest app rewards users with 'green energy points' for low-carbon actions such as walking to work. These points grow a virtual tree in the app, which Alipay matches by planting a real tree through partnerships.[1] Rather than merely performing existing tasks more efficiently, using AI for regeneration leverages its generative potential to undertake entirely new tasks, often in unexpected ways (Thomas and Tee 2022), thereby reimagining how firms approach environmental sustainability (Bohnsack, Bidmon, and Pinkse 2022).

The discourse on the relationship between AI and environmental sustainability is evolving rapidly. Several scholars have highlighted positive links between AI and environmental sustainability. Such discussions are often framed in relation to the concepts of green digital transformation or twin transition (Diodato et al. 2023; Faggian, Marzucchi, and Montresor 2024; Montresor and Vezzani 2023; Veugelers et al. 2023). Policymakers also increasingly stress that firms should leverage digital technologies, particularly AI (Calvino, Dechezleprêtre, and Haerle 2025; Manikandan et al. 2025), to enhance competitiveness while embracing green transformations. A prominent example is Europe's Green Deal, launched by the European Commission, which represents one of the most resource-intensive initiatives aimed at fostering the twin

[1] 'Alipay Ant Forest: Using Digital Technologies to Scale up Climate Action,' UN Climate Change, https://unfccc.int/climate-action/momentum-for-change/planetary-health/alipay-ant-forest (accessed January 30, 2026).

transition. As part of this effort, the Commission revised the 'EU industrial strategy to address the twin challenge of the green and digital transformation.'[2]

In summary, AI expands the possibilities for improving environmental sustainability (Holm et al. 2023; Lyu et al. 2025; Nishant, Kennedy, and Corbett 2020). However, this occurs against a backdrop of growing scrutiny regarding AI's negative environmental effects. Concerns are mounting that developing and deploying AI-based tools consumes substantial energy, water, and other natural resources across global supply chains (Lyu et al. 2025). Beyond these direct effects, Luccioni, Strubell, and Crawford (2025) identify a range of indirect and systemic effects, including rebound dynamics when efficiency gains drive further consumption, accelerate hardware turnover, and reshape user behaviour in resource-intensive ways. These insights suggest that AI's environmental implications are neither linear nor guaranteed to be positive, but contingent on how AI is deployed. To assess whether AI enhances or undermines environmental sustainability as part of the twin transition, it is necessary to unpack the effects AI generates at the firm level across different scopes of activity. In the next section, we develop a typology that systematically distinguishes the ways in which AI produces environmental sustainability effects.

3. Environmental sustainability effects of AI

Understanding AI's environmental effects requires moving beyond binary assessments of whether it is beneficial or harmful. Instead, we suggest that these effects unfold along three analytically distinct dimensions that detail how they arise and propagate over time. The first dimension concerns the *scope of firm activity* affected by AI. Synthesising recent advances (Kulkov et al. 2024; Luccioni, Strubell, and Crawford 2025), we distinguish between **direct effects** within existing activities of a firm for which AI is deployed, **indirect effects** that emerge within existing activities through behavioural, economic, or structural adjustments, and **generative effects** that arise when AI enables novel activities in forms that would not have been feasible without it. The second dimension is the *time horizon*, which runs across these effects. Direct effects tend to manifest soon after AI adoption. Indirect effects, by contrast, accumulate over a longer period of time as behavioural and structural adjustments take hold. Generative effects operate on the longest time

Table 1. Environmental sustainability effects of AI.

Scope of firm activity – Time horizon	Direction of AI	
	Positive effects	*Negative effects*
Direct Existing activity – short term	Efficiency effects – Reduced energy and resource use – Emissions optimisation and prediction – Improved monitoring and control *Examples*: smart building management, predictive maintenance for renewables	Footprint effects - Energy- and water-intensive computation – Material extraction for AI hardware - E-waste from rapid product and infrastructure turnover *Examples*: large-scale model training, data centre expansion,
Indirect Existing activity – medium term (accumulate over time)	Prebound effects – Performance exceeds expectations – Structural efficiency gains *Examples:* AI-based recycling systems, precision spraying in agriculture	Rebound effects – Increased usage volumes – Hardware and device turnover – Time and behaviour rebounds *Examples:* AI-driven content growth, faster device replacement cycles
Generative Novel activity – long term	Unlocking effects – New green activities – Green innovation and experimentation - System-level sustainability strategies *Examples:* digital twins for low-carbon design, regenerative nudging platforms	Path-escalating effects - New extractive or carbon-intensive activities - High-computational infrastructures embedded in structurally low-emission sectors - Enabled emissions (new carbon-intensive activities made feasible by AI) *Examples:* AI-supported fossil exploration, generative AI embedded in knowledge-intensive industries

[2]'The European Green Deal', European Commission, https://eur-lex.europa.eu/legal-content/EN/TXT/?qid=1576150542719&uri=COM%3A2019%3A640%3AFIN (accessed January 30, 2026).

horizon, reshaping the trajectory of firm activity rather than current operations. The third dimension concerns the *direction of AI*, where we distinguish between positive and negative effects of AI on environmental sustainability. Together, these dimensions yield a typology that captures how AI shapes environmental sustainability at the firm level (see Table 1). The remainder of this section elaborates on the six effects, using their analytical labels while situating each within the broader categories of direct, indirect, and generative effects.

3.1. Direct effects

Direct effects arise within the focal firm activity for which AI is deployed (e.g. environmental management, human resources) and tend to be short term. These effects are the most visible, most frequently measured, and often form the basis of sustainability claims associated with AI adoption.

On the positive side, efficiency effects (i.e. direct positive effects) occur when AI solutions reduce environmental harm within existing firm activities. A large body of research highlights AI's potential to improve resource efficiency, reduce emissions, and mitigate environmental harm through optimisation and prediction. For example, AI-based forecasting models can improve the prediction of extreme weather events such as droughts, floods, and wildfires, enabling earlier and more targeted interventions (Camps-Valls et al. 2025). AI has also been shown to enhance the efficiency of energy production and consumption, including applications in building energy management and grid optimisation (Dekeyrel and Fessler 2024; Nishant, Kennedy, and Corbett 2020; Zeng and Wang 2025). In these cases, AI strengthens established environmental management activities by making monitoring, analysis, and control more precise and cost-effective.

However, AI also produces footprint effects (i.e. direct negative effects) that increase environmental harm from existing firm activities. These effects stem from the energy intensity, water consumption, and material requirements associated with training and deploying AI systems. Large-scale models rely on energy-intensive data centres, consume significant volumes of freshwater for cooling, and depend on critical minerals whose extraction generates environmental harm (Crawford 2024; Li et al. 2025). Rapid hardware turnover further contributes to growing e-waste streams. These direct negative effects are not peripheral side issues; in many cases, they scale proportionally with AI adoption and intensify as AI systems diffuse across industries.

Whether the efficiency and footprint effects of AI have a net positive or negative effect depends on the scale of deployment, the energy mix of the underlying infrastructure, and the strategic choices firms make; a question that the literature has not yet resolved and that motivates the configurational analysis in Section 3.

3.2. Indirect effects

Indirect effects occur within the same existing domain of firm activity but not as an immediate consequence of AI's technical features. They emerge downstream of AI adoption rather than at the point of application. Unlike direct effects – which can be attributed to specific AI deployments and measured at the point of use –, they propagate throughout the firm and beyond, and often become visible only as adoption scales. The pathway through which they propagate, however, varies considerably: *behavioural channels* arise when individuals reallocate freed time or attention towards resource-intensive activities; *economic channels* operate through price-mediated demand expansion, where lower cost per unit stimulates higher total consumption; and *technological channels* involve changes to hardware cycles, infrastructure, and complementary assets that accumulate over time. The relative dominance of each channel varies with industry context, adoption scale, and time horizon, which means the boundary between indirect effect types is rarely sharp in practice, a heterogeneity our typology acknowledges rather than resolves.

On the positive side, prebound effects (i.e. indirect positive effects) include cases where AI delivers environmental benefits that exceed initial expectations. Prebound effects describe situations in which actual environmental performance exceeds what ex-ante efficiency estimates predicted, because system-level adaptation and learning amplify the initial benefit beyond the anticipated range (Sunikka-Blank and Galvin 2012). The term 'prebound' captures the phase before expectations are revised upward: realised performance already outpaces the original benchmark, but firms have not yet adjusted their plans or commitments to reflect this surplus. Early evidence suggests that AI can generate such effects in environmental contexts. For example, conventional recycling sorting in the United States are reported to have long stagnated at around 43% for aluminium cans, 31% for glass, and 5% for plastics. Using AI, the recycling technology providers AMP reports recovering more than 90% of reusable materials successfully. Moreover, their AI-based technology is also to handle garbage that traditional recycling facilities would not process, which generates new ecological value. This constitutes the prebound effect: the system delivers more than just improving existing recycling approaches, constituting a structural prebound effect in which the system's economic viability amplifies its environmental reach.[3] Similarly, AI-based optimisation of waste collection routes has been shown to increase plastic recovery efficiency in marine environments by more than 60 percent (den Hertog et al. 2025). And AI-based precision spraying technologies that distinguish crops from weeds are likely to reduce agrochemical use by up to 90 percent, according to reported field applications.[4]

At the same time, rebound effects (i.e. indirect negative effects) are well documented and occur when efficiency gains lower the cost, time, or effort required to perform an activity, thereby stimulating increased usage that offsets or even outweighs the initial environmental benefit (Berkhout, Muskens, and Velthuijsen 2000; Lange et al. 2021; Luccioni, Strubell, and Crawford 2025). Rebound effects take several distinct forms that differ in their scope. *Scale rebounds* occur when efficiency gains reduce per-unit cost and thereby stimulate higher total volumes of AI use, absorbing or reversing the initial efficiency dividend: cheaper inference encourages more queries, not fewer resources. *Technology turnover rebounds* arise when AI adoption accelerates the replacement of complementary devices – AI-ready smartphones, smart industrial equipment, or data centre hardware – generating material and energy footprints that compound across successive hardware generations. *Behavioural rebounds* emerge when AI automates routine tasks and frees time or cognitive capacity that is then reallocated to additional resource-intensive activities such as streaming, extended browsing, or content creation. These three forms are analytically distinct but frequently compound in practice: scale rebounds can trigger technology turnover, and behavioural rebounds amplify the demand effects that scale rebounds initiate (Luccioni, Strubell, and Crawford 2025).

Figure 1 maps these dynamics by decomposing each indirect effect into a cause – the layer that originates it – and an effect – the layer in which the environmental consequence lands. Three patterns emerge. First, most AI cases cascade across layers rather than remaining within one: technological causes frequently produce economic and behavioural effects, and economic causes propagate into technological and behavioural ones. Second, behaviour rarely forms the origin of specific effects but frequently absorbs them, which is why behavioural channels are dominated by rebound dynamics. Third, prebound and rebound trajectories can travel through any of the three channels, but they do so asymmetrically; prebounds typically appear in technological and economic channels, while rebounds are pervasive across all three. This asymmetry is part of what makes net outcomes structurally ambiguous.

Together, direct and indirect effects create a pattern in which the net environmental effects of AI adoption remain structurally ambiguous – an ambiguity that firms can resolve only through the deliberate configuration of how these effects are managed, a point developed further in Section 3.

3.3. Generative effects

Beyond modifying existing firm activities, AI also enables activities that were not previously feasible at all – not merely new ways of performing existing tasks, but qualitatively new domains of activity. This is the defining criterion of generative effects: they expand the production possibility frontier of the firm rather than shifting performance within it. Where AI changes how an existing activity is performed, the effect is direct or indirect; where AI enables an activity that did not exist before, the effect is generative. These generative effects reshape what firms and users are able to do, thereby expanding or transforming the space of possible activities. This generative capacity is consistent with AI's emerging character as a general-purpose technology. Generative AI in particular appears to exhibit the defining GPT characteristics of

[3] 'Recycling has been a flop, financially. AMP is using AI to make it pay of,' Fortune, https://fortune.com/2025/06/26/ai-recycling-trash-amp-robotics/ (accessed April 15, 2026).

[4] 'Targeted Spray Technology: Companies, Functionality and Benefits,' Montana State University, https://agresearch.montana.edu/narc/Programs_and_projects/narc-precisionag/precision-spot-spraying-technology.html (accessed April 15, 2026).

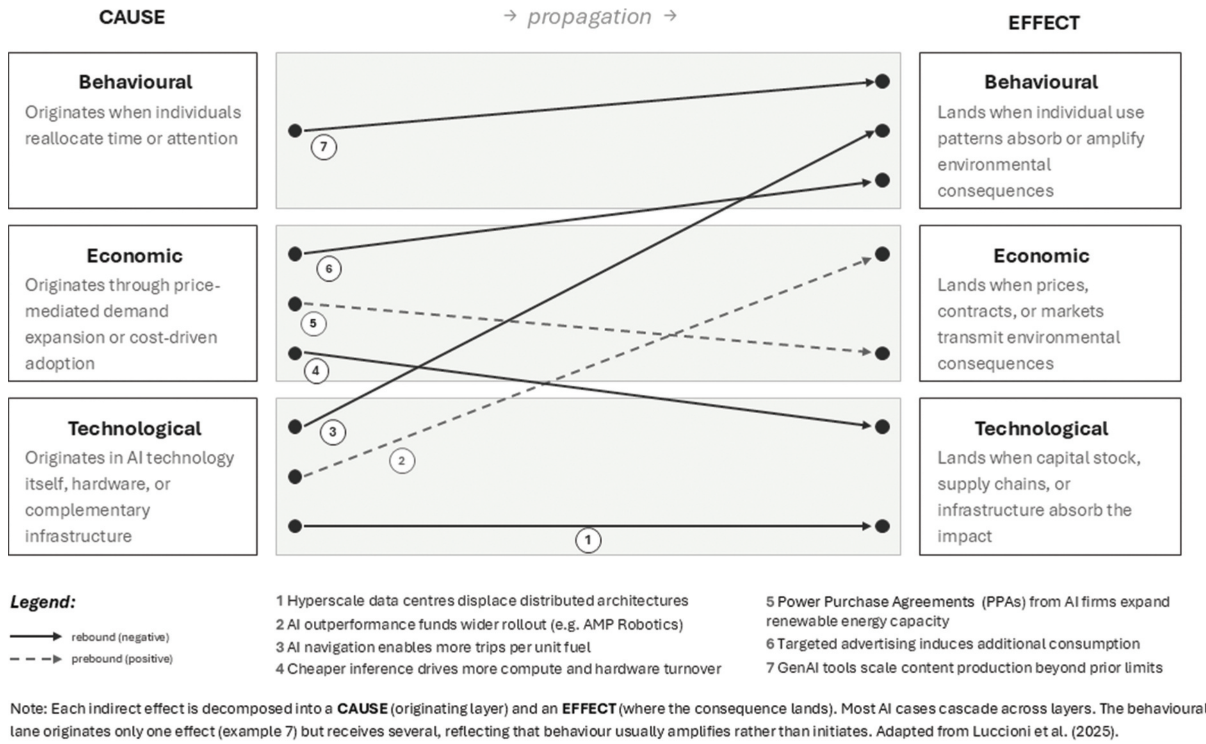

Figure 1. Cause-to-effect cascades in indirect environmental effects of AI.

pervasiveness, continuous improvement, and innovation spawning – the last of which directly underpins the unlocking effects developed below (Calvino, Haerle, and Liu 2025).

Unlocking effects (i.e. generative positive effects) arise when AI enables activities that contribute to environmental sustainability and that were not previously feasible. The criterion is feasibility, not efficiency: unlocking occurs when an activity crosses from the domain of the impossible to the domain of the possible. The mechanism through which this happens is adoption rather than innovation: firms access these benefits by deploying existing AI systems in new problem domains, without developing novel AI themselves. The deployment of existing AI systems in new problem domains – green product design, biodiversity measurement, regenerative logistics – is sufficient to unlock new sustainability-oriented activities. This distinguishes unlocking effects from more generic innovation effects and underscores their relevance for firms without dedicated AI research functions.

Research highlights AI's role in enabling new forms of experimentation, learning, and coordination. Falcke et al. (2026) argue that AI supports the development of digital representations and simulations that reduce the environmental burden of traditional product development processes that often are unnoticed (Bansal and Grewatsch 2020). Likewise, Montresor and Vezzani (2023) show that AI investments increase the likelihood that firms engage in green innovation relative to other digital technologies. Moreover, AI applications seem especially promising for putting regenerative sustainability into action and promote activities that restore and regenerate the natural environment (Hahn and Tampe 2020). Building on the example of Alipay's Ant Forest outlined above, consider Ecosia, a carbon-negative search engine that invests in reforestation, and the Mastercard Priceless Planet Coalition. In all these cases, AI's generative effects enable firms to pursue sustainability strategies that go beyond efficiency improvements towards novel forms of value creation.

Conversely, path-escalating effects (i.e. generative negative effects) occur when AI enables new environmentally harmful activities, giving rise to what also has been referred to as 'enabled emissions.'[5] These effects are not rebounds from efficiency gains but represent additional environmental harm made possible by AI's deployment. Examples include AI-supported mineral, oil, and gas exploration, where advanced analytics and sensing technologies allow firms to identify and exploit reserves that were previously

[5]'Enabled Emissions Campaign,' Enabled Emissions, https://www.enabledemissions.com/ (accessed January 30, 2026).

inaccessible. By lowering exploration risk and increasing extraction precision, AI can expand fossil fuel production and associated greenhouse gas emissions, even as other parts of the economy decarbonise (Luccioni, Strubell, and Crawford 2025).

A structurally distinct form of path-escalating effect is emerging in knowledge-intensive industries. Generative AI is increasingly substituting human cognitive labour in consulting, law, finance, and education, not by making existing tasks more efficient, but by replacing a structurally low-emission input with a high-computational one. Luccioni, Strubell, and Crawford (2025) show that generative AI inference produces orders of magnitude more emissions than the narrow, task-specific models deployed in industrial settings. As broad foundation models become embedded in the operational core of these industries, they create a new category of carbon-intensive activity in sectors that previously had no meaningful computational footprint. Unlike fossil exploration, where path-escalation deepens existing extractive trajectories, this case extends path-escalation into industries considered structurally clean. The environmental pressure does not intensify within a known carbon-intensive sector; it migrates into new ones, generating new carbon hotspots and complicating both measurement and policy. Because these commitments are embedded in workflow infrastructure and become progressively harder to reverse as adoption scales, the trajectory has the same lock-in character as other path-escalating effects.

Negative generative effects illustrate how AI can deepen unsustainable trajectories by opening up new types of environmental degradation rather than intensifying existing ones. It is worth noting that attributing path-escalating effects to AI requires care. These effects would not occur in the absence of AI's deployment – whether the exploration of previously inaccessible reserves or the structural embedding of high-computational inference in knowledge work – yet AI does not act autonomously; it is deployed in response to incentives. Path-escalating effects therefore, reflect a combination of AI deployment and strategic intent, an area we explore further in Section 3.

As we have shown, these six effects (see Figure 2 for an illustration) are analytically distinct. However, distinguishing them in practice – whether conceptually in a given organisational context or empirically in research – is challenging because they overlap, compound, and evolve over time. The value of the typology

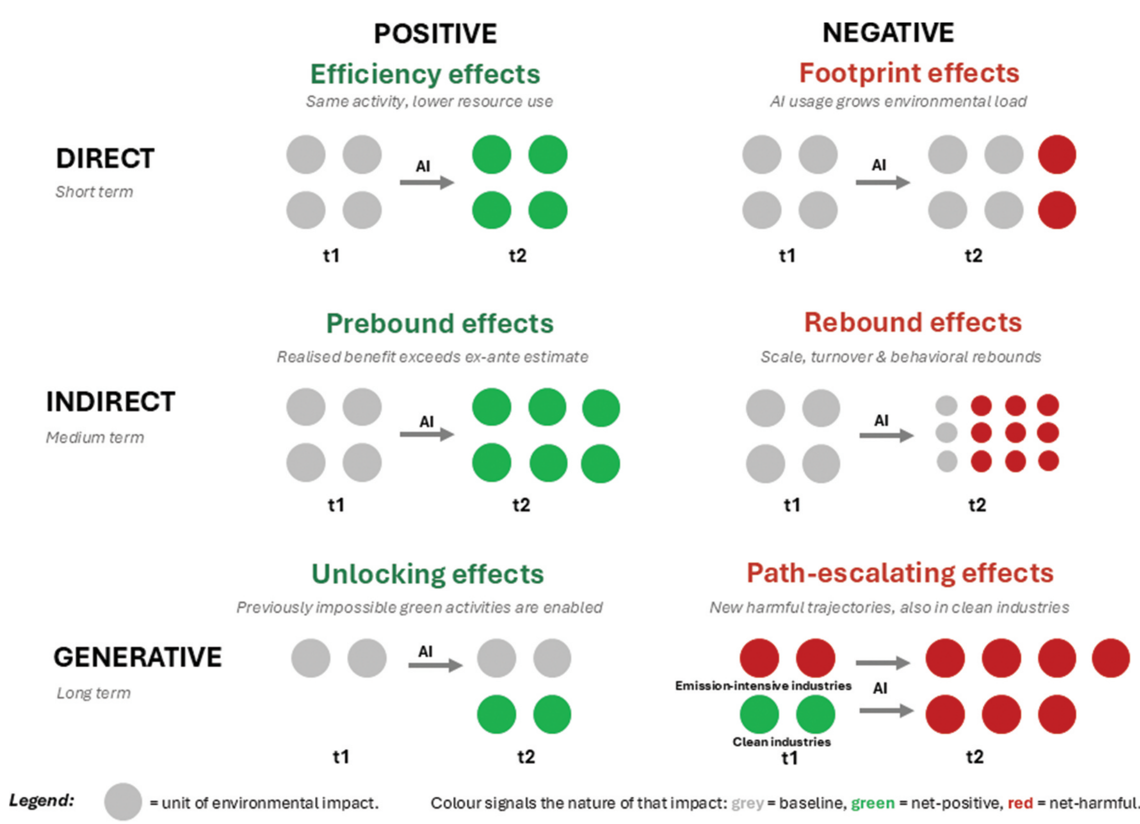

Figure 2. Illustration of the six environmental effects of AI.

lies not in offering a precise operationalisation but in laying the foundation for strategic questions firms should address when adopting AI; we turn to this aspect in the next section.

4. From effects to AI adoption configurations

AI is neither inherently beneficial nor harmful for the natural environment because environmental effects are not properties of the technology itself but emerge from two sources: how direct, indirect, and generative effects interact when AI is deployed, and how firms choose to strategically manage those interactions. A single AI application may simultaneously generate efficiency gains and rebound effects, or unlock new green activities while escalating footprint effects elsewhere. As recent advances highlight (Hutzschenreuter and Lämmermann 2025; Kocoglu and Mithani 2026; von Krogh, Ben-Menahem, and Shrestha 2021), AI's environmental effects depend on firms' strategic choices about the scale and scope of adoption and how tensions between positive and negative impacts are managed.

To clarify how firms' strategic choices interact with the six effects, we refer to these combinations as AI adoption configurations. Rooted in a longstanding tradition in management research where the variation of distinct elements is combined into configurations (Child 1972; Meyer, Tsui, and Hinings 1993; Reischauer, Güttel, and Schüßler 2021), the notion of configuration highlights how the effects of AI tend to combine with strategic choices. This perspective helps explain why similar AI-based technologies can lead to markedly different environmental effects. As recent studies point out, strategic choices related to AI involve multiple elements (Calvino, Dechezleprêtre, and Haerle 2025; Hutzschenreuter and Lämmermann 2025; Kocoglu and Mithani 2026; von Krogh, Ben-Menahem, and Shrestha 2021).

We propose that five elements provide an integrative understanding of how firms approach AI adoption: (1) the strategic objective of AI, that is, what management intends to achieve with AI (Hutzschenreuter and Lämmermann 2025); (2) the firm's strategic context, including its organisational and industry conditions, particularly whether sustainability is already a core strategic objective (Child 1972); (3) AI effects as outlined in Section 2; (4) strategic initiatives, defined as infrequent, top-management decisions that allocate resources when adopting technologies (Lee and Grewal 2004); and (5) guardrails, that is, restrictions on AI functionality designed to strategically prevent misuse and mitigate potential risks (Mills 2025). In the context of sustainability, guardrails encompass internal initiatives as well as the disclosure of information to external stakeholders (McGrath et al. 2021). Other aspects, such as industry, firm size, or AI maturity, may shape the intensity of these effects but do not alter their fundamental structure; they are therefore treated as contextual moderators instead.

Against this background, we propose three configurations of AI adoption: *sustainability-amplifying*, *productivity-stabilising*, and *harm-amplifying* (see Table 2). These configurations are dynamic for two reasons. First, firms may move between them as AI-based applications mature once deployed and strategies shift. Second, there is a temporal distinction between the three types of effects: direct effects manifest in the short term; indirect effects accumulate over months as behavioural adjustments propagate; and generative effects reshape a firm's activity portfolio over years. Firms that appear to occupy one configuration at a given moment may shift as adopted AI technologies mature, as negative effects intensify, or as their broader strategy evolves.

4.1. Sustainability-amplifying AI adoption

In the sustainability-amplifying configuration, the strategic objective of AI is to enable novel and systemic sustainability improvements that go beyond the optimisation of existing activities. Consider firms operating complex, energy- or resource-intensive activities, such as renewable energy production, large-scale food supply chains, or distributed infrastructure networks, where environmental performance is already a strategic priority. Here, AI is introduced to improve forecasting, coordination, and system-level optimisation, often beginning with pilot projects that promise both environmental and economic benefits. The first results are typically encouraging: energy use declines, waste is reduced, and performance improvements exceed initial expectations. More and more firms find themselves in this situation that reflects some of the most visible and widely cited applications of AI in sustainability contexts. Exemplary initiatives include

Table 2. AI adoption configurations.

Element	AI adoption configuration		
	Sustainability-amplifying	*Productivity-stabilising*	*Harm-amplifying*
Strategic objective of AI	Enable novel and systemic sustainability improvements that go beyond optimisation of existing activities	Improve efficiency and performance without large changes	Reduce uncertainty, accelerate throughput, or extend asset lifetimes in key activities
Dominant AI effects	– Efficiency effects – Prebound effects – Unlocking effects	– Efficiency effects – Rebound effects and footprint effects grow over time	– Footprint effects – Rebound effects – Path-escalating effects
Strategic context	Environmental performance is an industry priority (e.g. renewable energy production, food supply chains, hospitality) The firm seeks to accelerate sustainability progress beyond what conventional approaches allow.	Sustainability is present as a compliance obligation but is not a major industry-wide priority (e.g. professional services, finance, higher education, marketing) The firm faces competitive pressure to improve operational efficiency.	Sustainability is secondary as competitive advantage depends on resource throughput (e.g. oil, gas, mining) The firm faces economic incentives to expand its activities to which AI is applied. Knowledge-intensive industries whose AI adoption structurally embeds high-computational infrastructure may also migrate into this configuration over time.
Strategic initiatives	– Assimilation – Technology alliancing	– Selective optimization – Incremental experimentation with safeguards	– Avoid implementing such AI initiatives or radically redesign them
Guardrails	– Comprehensive monitoring of rebound effects – Realistic financial expectations – Periodic and balanced information disclosure	– Usage guidelines – Monitoring of AI-related footprint – Early and transparent communication of limits	– Identification of and interruption of rebound-driven illusions of progress – Heightened transparency

predictive maintenance for wind farms as pursued by Ørsted,[6] precision agriculture systems that reduce fertiliser and water use as focused by John Deere,[7] and distributed smart grids that optimise local energy flows that Iberdrola is experimenting with.[8]

As these examples show, there are multiple *dominant AI effects*. There are **efficiency effects** because of reducing resource use and emissions within focal activities. At the same time, **prebound effects** are likely, where realised performance improvements exceed ex ante expectations due to learning and system-level coordination. Ultimately, the aspiration over the long time is to establish and maintain **unlocking effects**.

The sustainability-amplifying configuration typically thrives in a *strategic context* where environmental performance has become a central industry priority – spanning industries such as renewable energy production and food supply chains – yet conventional approaches increasingly fall short of delivering the progress required. Moreover, firms in these industries face mounting pressure to accelerate their sustainability trajectories beyond what established methods can deliver (Kocoglu and Mithani 2026).

Two *strategic initiatives* are particularly relevant to adopt AI as part of sustainability-amplifying configurations. The first is **assimilation** (Zhu, Kraemer, and Xu 2006). This refers to a process where firms first develop and grow AI-initiatives within a business unit, geographic region, or portfolio once initial pilots demonstrate both environmental and economic value. They then replicate and adapt successful AI solutions across business units to amplify system-wide benefits. A prominent example of assimilation is Google DeepMind's data centre cooling system. After a pilot achieved a 40 percent reduction in cooling energy at one facility, Google rolled out the system across multiple data centres. Over time, the system evolved from providing human-implemented recommendations in 2016 to fully autonomous control in 2018, with claimed energy savings of around 30 percent.[9] Similar assimilation dynamics can be observed in the hospitality

[6]'Ørsted Builds a Greener World with Offshore Wind Power and Digital Technology,' Microsoft News, https://news.microsoft.com/source/features/digital-transformation/orsted-greener-world-offshore-wind-digital-technology/ (accessed January 30, 2026).

[7]„John Deere RevolutionisesRevolutionises Agriculture with AI and Automation," Assembly Magazine, https://www.assemblymag.com/articles/97831-john-deere-revolutionizes-agriculture-with-ai-and-automation (accessed January 30, 2026).

[8]'AI for Electricity Networks,' Iberdrola, https://www.iberdrola.com/about-us/what-we-do/smart-grids/ai-electricity-networks (accessed January 30, 2026).

[9]'Safety First AI for Autonomous Data Centre Cooling and Industrial Control,' Google DeepMind Blog, https://deepmind.google/blog/safety-first-ai-for-autonomous-data-centre-cooling-and-industrial-control/ (accessed January 30, 2026).

sector. Hilton Tokyo Bay collaborated with Winnow Vision to pilot an AI-based food waste reduction technology, achieving a claimed 30 percent reduction in food waste, equivalent to more than 17,000 meals saved annually. Following this pilot, the technology was scaled across multiple hospitality properties globally.[10] A further example is Walmart's Global Supply Chain Playbook. The retailer developed reusable AI solutions, such as 'self-healing inventory' systems and agentic AI tools, which are shared and adapted across operations in countries including Costa Rica, Mexico, and Canada. Local units can tailor these tools to their specific contexts while benefiting from improvements generated elsewhere on a shared infrastructure.[11]

The second strategic initiative that becomes salient after the first one is under way is technology alliancing, which refers to formal partnerships with external actors with the purpose to refine and expand the AI application (Nueno and Oosterveld 1988). Internal innovation oriented towards further efficiency gains remains possible within this configuration, though. Technology alliancing emerges as a distinct strategic initiative, however, because firms in sustainability-amplifying contexts typically encounter a ceiling on what they alone can achieve. Sustainability challenges such as supply chain emissions, grid-level coordination, or watershed management, extend beyond firm boundaries. Alliancing is therefore not a substitute for internal innovation but a mechanism through which internal advances are extended across organisational boundaries to generate system-level environmental gains. Walmart's 'Gigaton' initiative provides a telling illustration. Through this initiative, the retailer committed to removing one gigaton of emissions from its supply chain by 2030 by using AI-based tools. In collaboration with the Environmental Defense Fund and the World Wildlife Fund, Walmart provides suppliers with AI-enabled tools to track emissions, set reduction targets, and coordinate sustainability efforts across firm boundaries.[12] Here, AI's unlocking effects become particularly salient, as digital coordination enables sustainability initiatives that would be difficult to implement through firm-level action alone.

Three *guardrails* are especially relevant to avoid negative effects to unfold. First, firms need to engage in comprehensive monitoring of rebound effects that may offset environmental gains. Even low-risk, high-impact initiatives can increase overall resource consumption if efficiency improvements stimulate higher demand, greater throughput, or accelerated hardware upgrades. Rebound effects are the primary guardrail concern in the sustainability-amplifying configuration because they are structurally most likely to undermine initiatives that have already demonstrated environmental value. In this configuration, the positive effects – notably efficiency and prebound effects – are already delivering; the strategic risk is that such success stimulates an increase in demand that then erodes those gains. In particular, firms should track induced demand rebounds, scale rebounds, and technology turnover rebounds (Luccioni, Strubell, and Crawford 2025).

Second, firms should ensure that return on investment expectations remain realistic. Overly optimistic projections can encourage excessive investment or premature automation (Brynjolfsson, Rock, and Syverson 2017), increasing both footprint and rebound effects. Maintaining disciplined expectations helps prevent sustainability-amplifying configurations from drifting towards negative effects as AI systems diffuse and mature.

Third, with regard to strategic stakeholder communication, we advise engaging in periodic and balanced information disclosure rather than one-off announcements or static dashboards (McGrath et al. 2021; Reischauer and Ringel 2023). Firms should provide ongoing updates that highlight realised environmental gains, trade-offs, and learning processes over time. This approach helps maintain credibility and legitimacy, particularly as initiatives often involve iterative experimentation and changing system dynamics. Continuous communication is more effective than simplified performance metrics, which risk obscuring the complexity of transforming multiple interdependent activities simultaneously.

[10]'Hilton Tokyo Cut Food Waste with Winnow Vision,' Winnow Solutions Blog, https://blog.winnowsolutions.com/hilton-tokyo-cut-food-waste-with-winnow-vision (accessed January 30, 2026).
[11]'Walmart's U.S. Supply Chain Playbook Goes Global – and It's Reinventing Retail at Scale,' Walmart Corporate, https://corporate.walmart.com/news/2025/07/17/walmarts-us-supply-chain-playbook-goes-global-and-its-reinventing-retail-at-scale (accessed January 30, 2026).
[12]'Walmart Project Gigaton Win Shows How to Cut Emissions with Speed & Scale,' Environmental Defence Fund, https://business.edf.org/insights/walmart-project-gigaton-win-shows-how-to-cut-emissions-with-speed-scale/ (accessed January 30, 2026).

4.2. Productivity-stabilising AI adoption

In the productivity-stabilising configuration, the *strategic objective of AI* is to adopt it to improve efficiency and performance without fundamentally altering a firm's core business model, products, or sustainability strategy. AI is applied within existing activities and organisational structures rather than deployed to enable new categories of activity or to redefine competitive positioning.

As for the *dominant AI effects*, firms use AI to establish **efficiency effects** within existing activities. Examples include the use of generative AI tools for routine knowledge work, customer-facing chatbots in banking and insurance, and AI-driven back-office automation in universities and large service firms. While these applications frequently deliver economic benefits, their contribution to reducing a firm's environmental footprint is often limited or ambiguous. As such, the productivity-stabilising configuration reflects the prevailing assumption that digitalisation will automatically support sustainability, even when empirical evidence remains mixed. AI is deployed to draft documents, summarise reports, automate customer interactions, support internal decision-making, or streamline administrative workflows. This configuration is often perceived as low risk because they do not alter core products, markets, or business models. Accordingly, these applications currently represent some of the most widespread uses of AI across industries.

A related but higher-risk variant of this configuration emerges when firms pursue **prebound effects** through AI-enabled experimentation. Here, firms deploy AI in contexts characterised by substantial uncertainty and potentially large system-level effects, such as AI-enabled autonomous driving (Tesla and Waymo), large-scale energy balancing within smart grids (National Grid), or computational-intensive industrial optimisation (Schneider Electric). AI is used to explore performance frontiers, often with the expectation that realised improvements will exceed initial projections. While such experimentation can yield valuable insights and learning effects, it also introduces significant uncertainty, particularly when computational intensity, hardware requirements, and system scale increase rapidly.

The *strategic context* of this configuration, currently observable in industries like professional services, finance, higher education, and marketing, is one in which ecological considerations tend to be addressed primarily as regulatory requirements rather than as defining strategic concerns shared across the industry. The dominant strategic imperative is not sustainability leadership but rather staying competitive through making activities more efficient.

Two strategic initiatives are central to the productivity-stabilising configuration. The first is what we refer to as **selective optimisation** (Shrestha, Ben-Menahem, and von Krogh 2019). Firms should apply AI where efficiency gains clearly justify resource use and, where possible, redirect AI systems towards sustainability-supporting tasks rather than purely economic optimisation. For instance, Unilever used AI-based tools to improve its supply chain, achieving reported sales increases of 15–35 percent for retailers, improving energy efficiency in ice cream cabinets, and redesigning core products such as Cornetto ice cream to be more sustainable without altering taste.[13] Similarly, Goldman Sachs partnered with the MIT – IBM Watson AI Lab to advance AI-based biodiversity measurement using multimodal geospatial data from satellites and sensors, supporting the development of more robust conservation finance and nature-positive benchmarks.[14] Additional examples include Microsoft's use of AI to optimise internal data-centre energy management without altering core business models,[15] and Siemens' application of AI for predictive maintenance and process optimisation in manufacturing facilities,[16] where efficiency gains primarily stabilise existing production structures rather than transform sustainability trajectories. These cases illustrate that efficiency-oriented AI initiatives can contribute to sustainability objectives when paired with broader strategic commitments.

[13]'Unilever's Integration of AI in the Supply Chain,' AI Expert Network, https://aiexpert.network/case-study-unilevers-integration-of-ai-in-the-supply-chain/ (accessed January 30, 2026).

[14]'MIT-IBM Watson AI Lab,' Goldman Sachs Pressroom, 2024, https://www.goldmansachs.com/pressroom/press-releases/2024/mit-ibm-watson-ai-lab (accessed January 30, 2026).

[15]'DC Power and Energy Management,' Microsoft Research. https://www.microsoft.com/en-us/research/wp-content/uploads/2024/11/DC-power-and-energy-management-FINAL.pdf (accessed January 30, 2026).

[16]'Data, AI and Sustainability in Predictive Maintenance,' Siemens Blog, https://blog.siemens.com/2024/09/data-ai-and-sustainability-in-predictive-maintenance/ (accessed January 30, 2026).

The second strategic initiative is **incremental experimentation with safeguards** (Walmsley 2021). Rather than scaling AI applications aggressively from the outset, firms proceed in stages, pairing technical experimentation with clear rules, thresholds, and interfaces to be adjusted as AI-driven effects become better understood. Generative AI tools are particularly relevant in this context, as they enable teams and individuals with limited technical backgrounds to develop more concrete and tangible prototypes of ideas, moving beyond static visuals and text-based presentations. For example, utilities experimenting with AI-based demand forecasting often begin with sandboxed pilots that operate in parallel with existing control systems before allowing automated adjustments. Similarly, firms adopting generative AI for internal analytics or reporting frequently test multiple model configurations with capped usage limits and human oversight before broader deployment. While such experimentation can accelerate learning, it also increases the risk of rebound effects if successful prototypes are rapidly scaled without environmental oversight.

Guardrails are especially important in productivity-stabilising configurations because **rebound effects** tend to be pronounced. Firms in knowledge-intensive industries face a specific path-escalating risk: as generative AI substitutes human cognitive labour at scale, sectors that historically had no meaningful computational footprint may embed high-emission infrastructure into their operational core. This risk is structurally distinct from a rebound – it is not a consumption response to efficiency gains but a category shift in what these firms do. Guardrails should therefore address not only rebound dynamics but also whether AI adoption is creating new categories of environmental harm. Firms should therefore implement usage guidelines (Taeihagh 2021) for AI-based tools, potentially including limits or sanctions on unnecessary content generation.[17] For instance, firms may impose limits on large-scale text or image generation for non-essential internal use, prioritise task-specific models over multipurpose systems where feasible, or require justification for high-computational applications. Several public administrations and universities have already introduced internal AI usage policies that restrict unnecessary content generation and mandate monitoring of computational-intensive workloads.

In addition, continuous **monitoring of AI-related footprint** (Manikandan et al. 2025) is required to track real-time rebound effects, content-production rebounds, and induced demand. In higher-risk experimental contexts, guardrails should also address hardware turnover rebounds, scale rebounds, and behavioural rebounds, for example by capping usage, setting environmental thresholds, and incorporating adaptive monitoring mechanisms. These measures help prevent 'too good to be true' efficiency gains from masking systemic environmental harm as AI adoption scales.

Moreover, firms should focus on **early and comprehensive information disclosure** (Kocoglu and Mithani 2026; Reischauer and Ringel 2023). Firms are advised to articulate what AI-driven initiatives can and cannot achieve, how they relate to sustainability objectives, and where uncertainties remain. Given the often-localised and incremental nature of these initiatives, communication efforts can be more targeted than in the sustainability-amplifying configuration. However, particular emphasis should be placed on clarifying assumptions to avoid inflated expectations. The experience of Metaverse applications provides a cautionary counterexample. Framed as the 'future of digital connection' by Meta, many such initiatives have so far failed to deliver on their promises, illustrating how overconfident narratives can undermine credibility when outcomes fall short.

4.3. Harm-amplifying AI adoption

In the harm-amplifying configuration, the *strategic objective of AI* is to reduce uncertainty, accelerate throughput, or extend asset lifetimes in key activities. This reflects a relatively large spectrum of *dominant AI effects*. That is, AI adoption activates a combination of effects that systematically increase overall environmental damage. While **efficiency effects** may occur locally, they are outweighed by **footprint effects**, **rebound effects**, and, most importantly, **path-escalating effects** that generate new or expanded environmentally harmful activities. Examples include AI-supported mineral, oil, and gas exploration, where advanced analytics, sensing technologies, and predictive models reduce exploration risk and increase the economic viability of reserves that were previously inaccessible. By lowering uncertainty and improving

[17] 'Generative AI in Organizations,' Capgemini, https://www.capgemini.com/wp-content/uploads/2024/07/Generative-AI-in-Organizations-Refresh-1.pdf (accessed January 30, 2026).

extraction precision, AI enables firms to expand production volumes and extend the lifespan of extractive assets, even as other parts of the economy pursue decarbonisation goals (Luccioni, Strubell, and Crawford 2025). Path-escalating effects are not confined to traditionally carbon-intensive industries, however. The same mechanism, i.e. AI enabling a new harmful trajectory that would not otherwise exist, is now visible in sectors previously considered structurally clean. In such cases, AI does not merely optimise existing activities but reshapes the opportunity space in ways that deepen carbon lock-ins and amplify downstream emissions across supply chains. Similar dynamics can be observed in industries where AI becomes embedded in high-computational, high-throughput systems. The growing deployment of AI in autonomous mobility, for example, has been described as creating 'data centres on wheels,' with substantial energy and computational demands integrated directly into transport infrastructures (Sudhakar et al., 2023). Here, efficiency gains at the vehicle or system level coexist with behavioural rebounds, such as increased travel demand, and with scale effects that expand total system activity. The net result is an amplification rather than a reduction of environmental damage.

A parallel dynamic is emerging in knowledge-intensive industries. As consulting, law, finance, and education substitute human cognitive labour with broad generative models, they embed high-computational infrastructure in sectors previously considered structurally clean. The mechanism is path-escalating rather than rebound: these sectors are not consuming more in response to efficiency gains; they are creating a new category of carbon-intensive activity where none existed. The lock-in character is identical and workflow infrastructure becomes progressively harder to reverse as adoption scales.

We can expect this configuration to occur in two distinct strategic contexts. The first is industries where competitive positions are tied to the extraction and processing of natural resources, such as oil, gas, and mining, where sustainability is structurally subordinated to volume-driven business logic. The second is knowledge-intensive industries – professional services, finance, education, and similar – where generative AI adoption at scale creates path-escalating effects that may migrate these firms into harm-amplifying territory over time, even when their original intent was productivity stabilisation. The configurations are therefore not fixed: a firm that begins in a productivity-stabilising configuration can drift into harm-amplifying as foundation model adoption deepens and becomes embedded in operational infrastructure.

In the harm-amplifying configuration, *strategic initiatives* to prevent negative effects are relatively straightforward, albeit difficult to implement in practice. Firms should either **avoid implementing such AI initiatives or radically redesign them** to address underlying structural drivers of environmental harm rather than peripheral inefficiencies (Goos and Savona 2024).[18] For example, firms can redirect AI applications away from exploration towards applications such as grid resilience planning, methane leak detection, or operational remediation, where the objective is to reduce absolute environmental harm rather than expand extractive capacity.[19] Such meaningful redirection requires shifting AI use from expanding extractive capacity to managing decline, remediation, or transition activities. Incremental optimisation is insufficient in these contexts, as it risks creating the appearance of progress while reinforcing unsustainable trajectories.

Guardrails in this configuration focus on the **identification and interruption rebound-driven illusions of progress**. Illusional efficiency gains often increase material throughput, accelerate extraction, and induce demand across interconnected systems. Luccioni, Strubell, and Crawford (2025) show how AI used in exploration and extraction increases throughput and accelerates resource use across supply chains, even when local efficiency metrics improve. Effective guardrails therefore, require implementing exclusion or redirection rules based on scenario analyses that explicitly assess whether AI adoption amplifies core unsustainable processes, extends asset lifetimes, or increases absolute environmental pressure. Where such dynamics are detected, mechanisms should mandate a redirection towards less harmful applications or impose binding constraints, consisting of non-negotiable limits with respect to the natural environment rather than aspirational targets. Moreover, firms should commit to **heightened transparency**. Firms should clearly distinguish between genuine sustainability improvements and efficiency gains that merely delay,

[18]Kai Ebert, Nicolas Alder, Ralf Herbrich, and Philipp Hacker, 'AI, Climate, and Regulation: From Data Centers to the AI Act,' arXiv preprint arXiv:2410.06681, https://arxiv.org/html/2410.06681v2 (accessed January 30, 2026).

[19]'The AI-Enabled Utility: Rewiring to Win in the Energy Transition,' McKinsey & Company, https://www.mckinsey.com/~/media/mckinsey/industries/electric%20power%20and%20natural%20gas/our%20insights/the%20ai%20enabled%20utility%20rewiring%20to%20win%20in%20the%20energy%20transition/mck_utility_compendium-final.pdf (accessed January 30, 2026).

displace, or disguise deeper environmental problems. Ambiguous information disclosures that conflate reduced intensity with reduced effects erodes trust among regulators, investors, and civil society, particularly as enabled emissions become more visible over time.

5. Research implications and future research

By examining how AI shapes and enables twin transition initiatives, this paper contributes to two current debates in innovation and strategy research. First, we add to conversations on the *role of technological innovation for sustainability strategy*. While it is well established that green technologies and renewable energy sources improve the energy efficiency of production processes, and that digital technologies hold substantial strategic potential (Bohnsack, Bidmon, and Pinkse 2022; Pinkse, Demirel, and Marino 2024), the strategic effects of AI – an emerging general-purpose technology with distinct affordances (Holm et al. 2023) – are poorly understood. To address this gap, we propose a typology of six environmental effects of AI adoption: i.e. direct short-time effects (efficiency and footprint effects), indirect medium effects (prebound and rebound effects), and long-term generative effects (unlocking effects and path-escalating effects). The typology allows disentangling immediate efficiency gains from more slowly unfolding rebound effects, and incremental improvements from more profound changes. It supports analytical sensemaking by focusing on *how* environmental effects emerge and *where* they materialise. Direct, indirect, and generative effects differ in scope rather than intent, meaning that a single AI application may generate multiple effects simultaneously and that these effects may evolve as systems scale and usage patterns change. Our typology is particularly relevant to disentangle environmental impact of AI at the firm level, thereby complementing approaches on the industry level (Calvino, Dechezleprêtre, and Haerle 2025)

Second, we add to research on *firm-centric twin transitions*. While scholarship on twin transitions at the industry level has advanced understanding of the innovation and performance implications of these transitions (Diodato et al. 2023; Faggian, Marzucchi, and Montresor 2024; Gao 2024; Perri and Rocha 2024), only a few studies have detailed how firms can adopt digital technologies when transforming themselves to become greener and more digital (Veugelers et al. 2023). By examining AI's affordances and developing three AI adoption configurations – sustainability-amplifying, productivity-stabilising, and harm-amplifying AI adoption – we compare how these configurations differ across key elements: the strategic objective of AI, a firm's strategic context, dominant AI effects, strategic initiatives, and guardrails. Through this comparison, we bring nuance to discussions about the potential of AI to improve environmental sustainability at the firm level. We show that AI-based twin transitions can accelerate green transitions at the firm level by enabling efficiency gains, prebound effects, and unlocking new green activities. At the same time, they can reinforce unsustainable trajectories through rebound and footprint effects and path-escalating enabled emissions. Recognising these configurations – especially associated strategic initiatives and guardrails – helps move the debate beyond overly optimistic or pessimistic narratives and towards a more firm-centric understanding of when and how AI supports or undermines environmental sustainability efforts of firms. In doing so, we follow Hanisch (2024), who called for prescriptive theorising and conceptualising – an approach that devises, justifies, and enables alternate states; in our case, alternative states concerning the entanglement of green and digital transitions.

Like every study, ours comes with some limitations that provide promising starting points for *future research*. First, we focused on the effects of firms' AI adoption on the natural environment. However, given the profound impact of AI on society, our arguments should be connected to growing research on corporate digital responsibility that puts the spotlight on the interplay between business and social responsibility (Mueller 2022). Such a connection situates environmental effects within the broader societal obligations firms face when deploying AI.

Second, our conceptual analysis mainly considered firms with 'classic' business models, that is, firms that create value for customers by selling goods they produce or offering services. Yet many AI applications are deployed within firms operating under different logics, most notably platform-based models (Falcke et al. 2026; Holzmann et al. 2025), that also tend to cooperate with competitors (Reischauer and Hoffmann 2023). Future research should therefore examine how our insights translate to these new organisational forms and explore where conceptual adjustments may be necessary.

Third, because AI-based technologies evolve rapidly, we deliberately did not specify fixed time horizons for the effects we identify in our typology. Future research should develop clearer indicators for each of the six effect types, including where effects overlap, and examine how these indicators manifest across the different configurations. Relatedly, it would be interesting to identify how effects unfold in ecosystems, alignment structures shaped by interdependences in which firms co-innovate (Reischauer et al., 2025).

Fourth, our typology treats indirect effects as a single analytical category, but this category encompasses phenomena that differ substantially in mechanism – behavioural responses, economic price effects, and technological adjustments to hardware, infrastructure, and complementary assets. The typology developed in Section 2 and the cause-to-effect decomposition in Figure 1 begin to unpack these distinctions, but a more comprehensive sub-classification of indirect effects, potentially drawing on multi-level rebound frameworks (Lange et al. 2021), remains an open task. Future research could also develop finer-grained indicators distinguishing behavioural, economic, and technological indirect effects, examine how the relative weight of each channel shifts across industries, firm sizes, and stages of AI adoption, and investigate the structural asymmetry by which behaviour rarely forms the origin of indirect effects but frequently amplifies those originating elsewhere.

6. Practical implications and conclusion

The configurations and the effects they comprise developed in this paper support *managers* in diagnosing existing and planned AI adoption initiatives. One key implication is the need to operate a portfolio of AI initiatives across configurations. Firms are unlikely to pursue only sustainability-amplifying initiatives; instead, they typically combine efficiency-oriented applications, experimental deployments, and more ambitious system-level efforts. This aligns with prior work suggesting that firms should diversify their investments across a range of digital technologies, with a particular focus on AI applications (Diodato et al. 2023, 761). What matters is not the presence of a single 'best' initiative, but whether the overall portfolio of initiatives prevents rebound and path-escalating effects from dominating. Figure 3 illustrates the dynamic dimension of the configurations. Most firms enter at the productivity-stabilising configuration, where efficiency effects dominate, and rebounds accumulate over time. From this position, two diverging trajectories are possible. Firms that deploy deliberate sustainability strategies and implement guardrails can shift towards the sustainability-amplifying configuration. Firms that scale AI adoption without guardrails – including knowledge-intensive firms embedding generative AI in core operations – risk drifting towards the harm-amplifying configuration. Recognising which trajectory a firm is on, and intervening

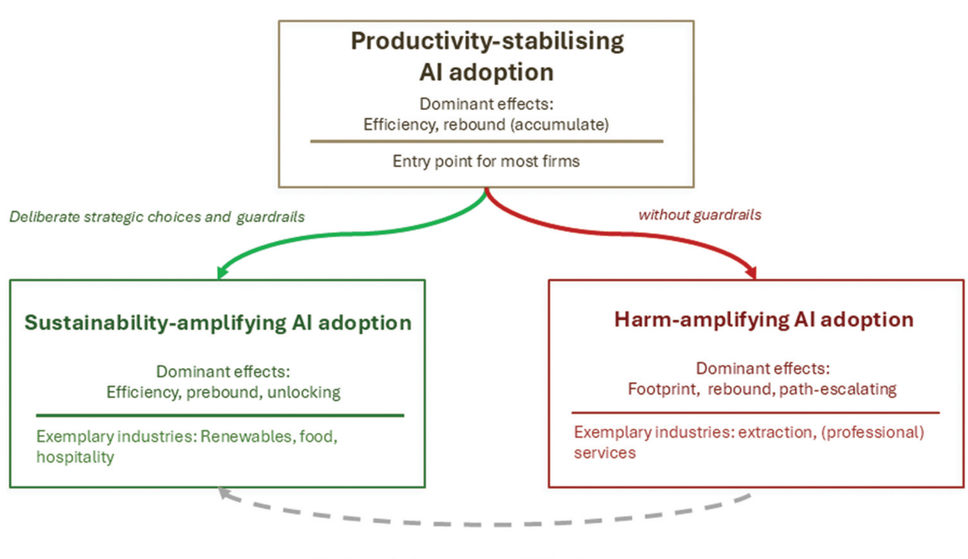

Figure 3. AI adoption configurations and drift dynamics.

Table 3. Diagnostic questions for AI adoption configurations.

Configuration	Guiding questions
Sustainability-amplifying	• Are environmental sustainability gains measurable and durable over time? • Do prebound or unlocking effects reinforce initial efficiency gains? • Does ROI justify scaling without inducing rebound effects? • Are guardrails in place to monitor system-level effects as initiatives expand?
Productivity-stabilising	• Is the initiative primarily optimising the status quo? • Are efficiency gains likely to trigger time, scale, or content rebounds? • Can the application be redirected towards sustainability-supporting tasks? • Are small efficiency wins being mistaken for structural transformation?
Harm-amplifying	• Does AI adoption prolong or intensify unsustainable carbon lock-ins? • Are enabled emissions likely to outweigh local efficiency gains? • Is the initiative addressing root causes or peripheral optimisation? • Are there clear thresholds or exclusion rules to prevent amplification of environmental harm?

before lock-ins with negative effects deepen, is the central managerial task the configurations framework is designed to support.

A further practical implication is the need for a dual assessment logic across all AI initiatives. Managers should evaluate projects not only in terms of return on investment, but also in terms of their potential to trigger rebound effects, enabled emissions, and other systemic environmental risks. Efficiency gains alone are insufficient indicators of environmental sustainability, particularly when AI adoption scales rapidly or becomes embedded in high-throughput systems. Table 3 provides a set of diagnostic questions aligned with the configurations identified in this paper. These questions are intended to support reflective decision-making rather than categorical judgement and help managers identify when initiatives may need additional guardrails, redirection, or escalation towards more ambitious sustainability objectives.

For *policymakers*, the implications differ in emphasis. Rather than primarily promoting or inspiring AI-based sustainability initiatives, policymakers should focus on observing, evaluating, and enforcing risk-calibrated guardrails that shape how firms deploy AI. This includes monitoring rebound dynamics, assessing enabled emissions, and ensuring that AI adoption does not undermine planetary boundary objectives through efficiency-driven lock-ins. In this sense, policy interventions are most effective when they target general conditions and constraints, rather than individual technologies or use cases.

In closing, this paper advances an integrated view of how AI shapes the twin transition at the firm level. By distinguishing direct, indirect, and generative effects and showing how they interact, we explain why AI's environmental effects depend not only on technical characteristics but also, critically, on firms' strategic choices. The promise of AI for the twin transition will be realised only if technological ambition is paired with careful strategic thinking, especially regarding the implementation of robust guardrails that ensure AI adoption supports, rather than undermines, environmental objectives.

Acknowledgements

We greatly thank Alessandra Perri, Vera Rocha, the reviewers, reviewers for the GRONEN 2026 Conference, and attendees of the Academy of Management Meeting 2025 for their constructive feedback on earlier drafts of this paper.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This work was supported by the COMET-K2 Center of the Linz Center of Mechatronics.

AI disclosure statement

We acknowledge the use of Anthropic's Claude Opus 4.6 to summarise notes from discussions among authors, to brainstorm, to support the generation of Figures, and to proofread.

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