



Productivity Narratives and Environmental Blind Spots: A Systematic Review of How Organizations Weigh Environmental Criteria When Adopting Generative AI

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ABSTRACT: Generative AI (GenAI) spreads through organizations faster than any shared method for weighing its environmental cost. Two literatures study the phenomenon from opposite ends. Adoption research explains why firms take up GenAI; environmental research measures the energy, water, and carbon it consumes. Whether the first treats the findings of the second as decision criteria remains unexamined. This systematic review asks how organizations incorporate environmental criteria into GenAI adoption and tests the proposition that productivity and modernization narratives dominate adoption and limit environmental governance. A TITLE-ABS-KEY search combining GenAI, adoption, and environmental terms yielded a corpus of 59 sources; main findings were extracted for 46 and grouped by the role each study assigns to the environment. Fourteen studies explain adoption through readiness, institutional pressure, top management support, and ethical leadership. None records ecological cost as a determinant, while six model ethics explicitly. Eleven studies treat environmental performance as an outcome of adoption. Twenty-one measures the environmental burden or proposes instruments to govern it, yet only six tie those instruments to organizational decisions. The evidence supports the proposition with one qualification: environmental criteria are absent from adoption models, which is different from absent from practice. The review separates two meanings of "environmental" that the literature conflates, consolidates candidate decision criteria, and sets an agenda for testing ecological cost as an antecedent of adoption.

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1. INTRODUCTION

A large generative model can consume up to 4,600 times more energy than a traditional model (Desroches et al., 2025). Training a single GenAI model each year could produce environmental damage comparable to that of entire polluting industrial sectors (Ruggeri et al., 2025). In the United States, AI servers could generate significant water and carbon footprints, and reaching net-zero emissions by 2030 would require a faster energy transition (Xiao et al., 2025). These are sector-scale figures. The firms, banks, insurers, and public agencies that create the demand behind them enter the adoption of literature through a different door, one that opens onto readiness, competitive pressure, and performance.

Adoption studies are thorough and consistent as far as metrics are concerned. The most important factor influencing the adoption of technology in the banking sector in Vietnam is the preparedness of the organization. In addition, the assistance of the government and competitive forces further drive adoption (Ajili et al., 2025). In insurance firms, executive endorsement strongly influences implementation (Xu et al., 2025). Institutional influences and ethical standards force organizations to adopt GenAI, which in turn improves their performance (Rana et al., 2024).

The adoption process later cultivates exploratory and exploitative innovation (Khan et al., 2024; Singh et al., 2024; Zada et al.,

2024). Ethics appear consistently as a concept: ethical leadership influences the effect of adoption on performance (Kumar et al., 2025), and ethical governance is more strongly associated with sustained competitive performance than technology adoption alone (Alves et al., 2026). This enumeration does not include the ecological cost of technology.

Were environmental literature to engage adopters, the importance of that silence would be diminished. Generally, it does not. Footprint analysis is on data center architecture, model choice, and grid carbon intensity (d'Orgeval et al., 2026), user devices and networks (Berthelot et al., 2025) and measurement methodologies (Kim et al., 2026). They explain what happens after the system is implemented, and they give little insight into the decision-making process that led to its introduction in an organization.

Two obstacles make that decision harder to reach. The costs stay largely hidden from the buyer, spread across energy, water, and material consumption that call for full-cost accounting (Bozkurt, 2025), and carbon accounting for AI still lacks standardized protocols (Kim et al., 2026). The word "environmental" also means different things in the two literatures. In adoption studies, it often refers to a group of contextual factors; in footprint studies it names energy, water, and carbon. No synthesis has crossed the two.

The timing raises the stakes. In one national research network, most institutions remain in the experimental phase of GenAI deployment, and their primary concerns are data security, lack of clinician trust, and AI bias (Idnay et al., 2024). We argue that experimental phases are when evaluation routines take shape. Organizations that build those routines around security, trust, and bias will inherit them when deployment scales.

Oliveira et al. (2026) find that AI-related environmental impacts are substantial and context-dependent, and they call for systemlevel governance that brings energy and carbon constraints into design and operational decisions. Whether adopting organizations to carry such constraints into their own evaluation is the question this study takes up.

This study examines the environmental criteria considered in the adoption and evaluation of generative AI in organizations. It asks how organizations incorporate environmental criteria into that process. The review starts with a working proposition: GenAI adoption is guided predominantly by narratives of productivity and modernization, and this limits the integration of environmental criteria into organizational governance. Drawing on a corpus of fifty-nine sources, we map the role the literature assigns to the environment, test the proposition against that map, and identify where the evidence is thin.

II. LITERATURE REVIEW

2.1 Adoption models: rich in organization, silent on ecology

The adoption literature gives organizational conditions heavy weight, though it disagrees on which conditions matter. Readiness leads in Vietnam's banking sector (Ajili et al., 2025). Top management significantly influences adoption in insurance companies, while perceived compatibility does not (Xu et al., 2025). In public sector organizations, compatibility does matter, alongside perceived usefulness, ease of use, relative advantage, and top management support, and national context play a significant role (Mercuri et al., 2025).

A variable that counts in one sector and not in another limits any attempt to carry a determinant list across settings. Studies of financial services and of ChatGPT-type tools sort determinants into technological, organizational, and environmental groups (Agrawal, 2023; Yuan et al., 2025), and a multicriteria study validated by experts identifies organizational factors as critical for adoption in companies (Alcalá et al., 2025). Wider reviews and strategy-oriented work map GenAI in business and its organizational impacts (Şahin & Karayel, 2024; Smith, 2025).

Institutional and ethical motives also appear. Institutional pressures and ethical principles lead organizations to adopt GenAI and, through adoption, to better performance, with organizational innovativeness moderating the effect (Rana et al., 2024). In B2B firms, adoption is influenced by uniqueness, information completeness, convenience, and deceptiveness, and ethical leadership moderates the performance effect (Kumar et al., 2025). Executives describe GenAI as a decision-support and innovation amplifier rather than an autonomous decisionmaker, and they link ethical leadership to public trust, workforce well-being, and organizational legitimacy (Varouchas, 2026).

The dependent variables fall into two families: intention or uptake, and performance. GenAI can facilitate exploratory and exploitative innovation in manufacturing firms (Khan et al., 2024), and in FinTech it improves both kinds of innovation without significantly affecting ethical dilemmas (Zada et al., 2024). Across organizations more broadly, environmental dynamism and ethical dilemmas moderate the link between adoption and innovation (Singh et al., 2024).

The critical observation concerns what is missing. These models are rich in organizational and ethical constructs. None of the extracted findings lists energy, carbon, or water among the determinants of adoption. Where the word "environmental" appears, it labels a group of contextual factors or a moderator (Singh et al., 2024; Yuan et al., 2025), not the ecological cost of the technology being adopted.

2.2 The environmental burden of GenAI and the disagreement over its size

Footprint studies converge on one point and split on another. They converge on the claim that the burden is real and hard to see. AI related environmental impacts are substantial and context-dependent (Oliveira et al., 2026). Large generative models consume up to

4,600 times more energy than traditional models (Desroches et al., 2025), and training one model annually could produce impacts comparable to entire polluting industrial sectors (Ruggeri et al., 2025).

The costs are beyond servers. User terminals and networks add to the damage (Berthelot et al., 2025), and the hidden costs include energy, water, and material consumption (Bozkurt, 2025). GenAI and quantum computing both carry high impacts through energy demand and rare-material requirements (Esho et al., 2026). Energy consumption has drawn its own assessment (Friday & Ali, 2024), benchmarks now exist for the energy, water, and carbon footprint of LLM inference (Jegham et al., 2025), and the relation between financial investment in AI-based technologies and carbon footprint has been examined in selected advanced industrial economies (Konat et al., 2026).

Geography and design shape numbers. A life cycle analysis of several data center typologies finds that high-density, liquid-cooled designs yield the lowest environmental cost per e FLOP, and that model choice, geographic location, and grid carbon intensity all influence the footprint (d'Orgeval et al., 2026). In the United States, net-zero for AI servers by 2030 depends on accelerating the energy transition and using the clean energy potential of Midwestern states (Xiao et al., 2025). Usage intensity matters as well, because high-volume queries require more energy and water (Antoniuk & Koliada, 2025).

One study reads the evidence differently. Sidorkin (2025) reports that GenAI has a small carbon footprint and uses small amounts of fresh water, and that energy-efficient designs, renewable energy, and greater transparency can mitigate both. The reviewed studies do not share an accounting boundary. Some count the annual training of a model (Ruggeri et al., 2025), some the deployment of servers across a national grid (Xiao et al., 2025), and some the energy use of large models against traditional ones (Desroches et al., 2025). A decisionmaker who hears both the small-footprint message and the sector-scale message can reasonably conclude that the question is unsettled and move on.

2.3 GenAI as problem and as instrument

A second debate asks whether GenAI harms or helps the environment, and the answer changes with the level of analysis. At the aggregate level, AI significantly reduces ecological footprints and carbon emissions and promotes energy transitions, with the largest effect on energy transitions (Wang et al., 2024). The AI–EKC nexus for SDG 7 and SDG 13 has its own investigation (Wang et al., 2025), and the joint impacts of AI and public environmental concern on green innovation transformation in energy-intensive enterprises have been examined (Zhao & Li, 2025).

At the organizational level, GenAI integration improves environmental performance through enhanced ESG sensemaking, although excessive sustainability-related information weakens the gain and regulatory uncertainty amplifies it (Bag et al., 2026). Firms with stronger digital transformation, innovation, and marketing capabilities can enhance their adoption of GenAI and reach better market and sustainability performance (Joshi et al., 2026).

Supply-chain research reports parallel gains. Higher technology readiness improves circular and sustainable supply chain performance, though it may not raise efficiency (Malhotra & Manzoor, 2025). Digital dexterity improves decision quality and efficiency in sustainable supply chains, with an ethical factor amplifying the effect and regulatory governance shaping performance (Liu et al., 2026).

Government and policy support, top management support, and strategic leadership enable GenAI for green and responsible supply chains (Jamwal et al., 2026), and platforms with lean themes are perceived as the most sustainable, followed by green and circular themes (Singh et al., 2026). Related work addresses GenAI decision support for environmental and social supply chain sustainability (Ellahi et al., 2025), risk management for sustainable development projects (Mohamed et al., 2026), and the roles of innovation and AI regulation in the sustainable performance of manufacturing firms (Shen & Badulescu, 2025).

Green innovation recurs as a transmission channel. Green entrepreneurial leadership improves AI-driven green process innovation, with gains in financial and environmental performance in the Traditional Chinese Medicine industry (Liu et al., 2025). Zhou and Bu (2025) examine how green innovation channels the path from AI to energy reduction and corporate sustainability, and GenAI can foster green innovation and knowledge exchange even though ethical concerns remain (Liccardo et al., 2025).

GenAI can also serve environmental assessment. It can address data scarcity, enhance model scalability, and promote participatory decision-making, provided it is combined with hybrid modeling, participatory data governance, and sustainable AI infrastructures (Rahman et al., 2026). At the level of individuals, GenAI use indirectly shapes eco-conscious behavior through environmental attitudes, perceived impact, climate change anxiety, and awareness (Laachach & Sadiku-Dushi, 2026).

Two studies temper this optimism. AI solutions built for environmental purposes may carry hidden negative impacts, including increased greenhouse gas emissions (Ligozat et al., 2022), and decarbonizing electricity will not by itself solve the sustainability problems of GenAI services (Berthelot et al., 2025). The critical reading is that most of this evidence measures a benefit: the environmental gain that the adopting organization, or the environment through the tool application, receives.

The tool's own footprint is the object of study in only a few places. An organization can therefore regard itself as a green adopter without holding a single figure for what its adoption costs.

2.4 Instruments for governing the footprint

A third body of work supplies instruments. Green AI research has matured, and its authors consider it ready for adoption and industrial implementation (Verdecchia et al., 2023). Green AI is more environmentally friendly and more inclusive than conventional

AI, since it allows high-quality research without costly cloud servers (Bolón-Canedo et al., 2024). Tabbakh et al. (2024) propose a comprehensive framework that balances performance and resource efficiency through model optimization and efficient algorithms. Rojahn and Grum (2026) require a life cycle approach that links phase-explicit mapping with system levers and calibrated measurement across energy, carbon, water, and embodied impacts. Malik (2025) offers a Green AI benchmarking framework and invites developers to certify energy-efficient models. Kim et al. (2026) call for standardized measurement protocols that cover user behavior and life-cycle monitoring, and Elbouknify et al. (2026) find that Green AI in finance can balance performance, compliance, and environmental sustainability but needs standardized benchmarks and assessment tools. Oyewole and Joseph (2025) address energy-efficient techniques for reducing the environmental impact of large-scale models.

A smaller set of studies moves closer to organizational decisions. Antoniuk and Koliada (2025) propose a sustainability index to balance efficiency against the resources spent. Alonso-Robisco et al. (2026) show that operational constraints and decision-rule prompts can lower the carbon footprint of GenAI in economic research workflows, with human-in-the-loop governance safeguarding both productivity and environmental efficiency.

Wicaksono and Riharjo (2025) argue that organizations should integrate digital sustainability, ethical AI governance, and environmental responsibility into corporate strategy so that GenAI becomes a solution and not a threat to the climate crisis. At the end of the policy, work on public action for sustainable generative AI systems (Goff, 2024) and on an ecosystem-wide approach to green GenAI (Helms et al., 2025) widens the frame beyond the single firm. Desroches et al. (2025) add that net-zero goals require coordinated efforts across the AI value chain.

Most of these instruments address developers, infrastructure operators, or policymakers. The adopting organization, the party that buys, configures, and scales the tool, appears in a minority of them.

2.5 Where this study positions itself

Three gaps follow the debates above. Adoption models leave out the ecological cost of the technology. Footprint studies rarely address the adoption of decisions. And the benefit-side evidence on sustainability performance does not indicate whether adopters ever look at the cost side. This review advances literature in three ways. It reads the two bodies of work against each other. It distinguishes four roles literature gives to the environment: contextual factor, performance outcome, burden to be measured, and object to be governed. And it tests, against the extracted evidence, the proposition that productivity and modernization of narratives limit environmental governance in adoption.

III. RESEARCH METHODS

3.1 Design

This study is a systematic literature review. It is organized around one objective, one research question, and one working proposition. The objective was to examine the environmental criteria considered in processes of technology adoption and evaluation processes. The research question was: How do organizations incorporate environmental criteria into the adoption of GenAI?

The proposition held that the adoption of GenAI in organizations is guided predominantly by narratives of productivity and modernization, which limits the effective integration of environmental criteria into their governance. The proposition served as the reference against which the extracted evidence was read.

3.2 Search strategy

Records were identified with the following query, written in TITLE-ABS-KEY field syntax. It joins three concept blocks with AND: GenAI terms, adoption and decision terms, and environmental terms.

TITLE-ABS-KEY(("generative AI" OR GenAI OR "large language model*") AND ("technology adoption" OR "organizational adoption" OR "digital transformation" OR "implementation decision*") AND ("environmental criteria" OR "environmental impact*" OR "carbon footprint" OR "energy consumption" OR "water footprint" OR "life cycle assessment" OR "Green AI" OR sustainability))

Within each block, terms were combined with OR. Truncation (*) captured variants of "large language model", "implementation decision", and "environmental impact". The environmental block covers environmental criteria and impacts, carbon and water footprints, energy consumption, life cycle assessment, Green AI, and sustainability.

3.2.1 Eligibility criteria.

A source qualified if it (1) addressed GenAI or large language models, or AI and Green AI research bearing directly on the environmental footprint of such systems; (2) examined organizational adoption, implementation, or digital transformation, or examined the environmental impact, measurement, or governance of AI; (3) appeared as a journal article, conference paper, or preprint with a DOI; and (4) was written in English. No restriction on study design applied, so empirical, modelling, review, and conceptual work all qualified. Sources that addressed neither organizational uptake nor environmental impact were not retained.

3.2.3 Screening and retention.

Records surfaced by the tools were assessed against these criteria based on their titles, abstracts, and study-level summaries, and the retained corpus was fixed at 59 sources. The tools do not export the number of records identified and screened in a form that supports

a PRISMA flow diagram, so this review reports the retained corpus and not a record flow; Section 6.2 discusses the consequence. Retrieval closed in august 2026, and the retained corpus spans publication years 2022 to 2026.

3.3 Corpus and data extraction

The final corpus contains fifty-nine sources, all written in English and all carrying a DOI. Forty-five were published in 2025 or 2026, eleven in 2024, two in 2023, and one in 2022. Of the 59, 51 are journal articles, three are conference papers, four are ArXiv preprints, and one appeared in the AI-EDU Arxiv series. The application contexts include banking, insurance, FinTech, B2B firms, manufacturing, the public sector, clinical and translational science, supply chains, the Traditional Chinese Medicine industry, economic research workflows, and data centers.

For forty-six sources, the main finding was recorded in a review matrix as a one-sentence, study-level statement produced through the tools' structured summaries and linked to its source record. The statement is the unit of analysis: this manuscript attributes to a study nothing beyond its extracted statement. The remaining thirteen sources belong to the reference set, but the matrix holds no extracted finding for them. This manuscript cites those thirteen only for the scope stated in their titles and attributes no findings to them. Bibliographic metadata were checked for internal consistency across year, volume, and DOI, and the three records that showed discrepancies were corrected against publisher records.

3.4 Analytical procedure

Each of the forty-six extracted findings was assigned to one of four groups according to the role it plays for the environment:

- *Group A, adoption determinants, and deployment concerns*: the finding explains uptake, intention, performance, or concerns with organizational, institutional, or ethical factors.
- *Group B, environmental performance as outcome*: the finding reports sustainability or environmental gains attributed to GenAI.
- *Group C, environmental burden*: the finding quantifies or characterizes the footprint of GenAI.
- *Group D, instruments, and governance*: the finding proposes a framework, metric, benchmark, or rule for reducing or accounting for the footprint.

Assignment followed the primary focus of each finding. Two further codes were applied across groups: whether the study includes an ethical construct, and whether it connects environmental cost to an organizational decision. The proposition was then evaluated against three observable patterns: (1) whether ecological cost appears among the determinants in adoption studies; (2) whether environmental considerations enter mainly as outcomes instead of costs; and (3) what share of the burden and instrument studies connect to organizational decisions. The corpus mixes designs and sectors, so the synthesis is narrative and no effect sizes were pooled.

Classification was performed by the authors with the assistance of a GenAI model (Claude, Anthropic), which proposed assignments from the extracted statements and the group definitions; the authors reviewed the assignments. A single coding pass was used, and no inter-rater agreement statistics were computed. Table 1 lists the assignment of every study, so readers can inspect and contest each one.

Quality appraisal. No scored risk-of-bias instrument was applied because the corpus combines empirical, modelling, review, and conceptual designs for which no single instrument fits. Appraisal took two other forms: the type of each source was documented (Section 3.3), and conclusions that rest on one study are identified as such in the Discussion and in Section 6.2.

IV. RESULTS

4.1 Distribution of the corpus

Table 1 shows how the forty-six extracted findings distribute across the four groups.

Table 1: Extracted findings by the role assigned to the environment

Group	Role of the environment	n	Studies
A	Adoption determinants and deployment concerns	14	Agrawal (2023), Alcalá et al. (2025), Alves et al. (2026), Idnay et al. (2024), Khan et al. (2024), Kumar et al. (2025), Mercuri et al. (2025), Rana et al. (2024), Singh et al. (2024), Varouchas (2026), Xu et al. (2025), Ajili et al. (2025), Yuan et al. (2025), Zada et al. (2024).
B	Environmental performance as outcome	11	Bag et al. (2026), Jamwal et al. (2026), Joshi et al. (2026), Laachach & SadikuDushi (2026), Liccardo et al. (2025), Liu et al. (2025), Liu et al. (2026), Malhotra & Manzoor (2025), Rahman et al. (2026), Singh et al. (2026), Wang et al. (2024).

C	Environmental burden	11	Berthelot et al. (2025), Bozkurt (2025), Desroches et al. (2025), d'Orgeval et al. (2026), Esho et al. (2026), Friday & Ali (2024), Ligozat et al. (2022), Oliveira et al. (2026), Ruggeri et al. (2025), Sidorkin (2025), Xiao et al. (2025).
D	Instruments and governance	10	Alonso-Robisco et al. (2026), Antoniuk & Koliada (2025), Bolón-Canedo et al. (2024), Elbouknify et al. (2026), Kim et al. (2026), Malik (2025), Rojahn & Grum (2026), Tabbakh et al. (2024), Verdecchia et al. (2023), Wicaksono & Riharjo (2025).

Note. n = number of extracted findings per group (N = 46). Source: authors' elaboration based on the review matrix, extracted through Consensus, Elicit, and Research Rabbit.

4.2 Group A: adoption determinants and deployment concerns

The fourteen studies cover B2B firms (Alves et al., 2026; Kumar et al., 2025), banking (Ajili et al., 2025), financial services (Yuan et al., 2025), FinTech (Zada et al., 2024), insurance (Xu et al., 2025), manufacturing (Khan et al., 2024), the public sector (Mercuri et al., 2025), clinical and translational science (Idnay et al., 2024), and organizations more generally (Agrawal, 2023; Alcalá et al., 2025; Rana et al., 2024; Singh et al., 2024), plus an executive-level qualitative study (Varouchas, 2026).

The reported determinants are organizational readiness, competitive pressure, government support, top management support, institutional pressure, ethical principles, perceived usefulness, ease of use, relative advantage, and compatibility. Results diverge on compatibility: it matters in the public sector (Mercuri et al., 2025) and does not significantly influence adoption in insurance (Xu et al., 2025).

Six studies include an explicit ethical construct: ethical leadership (Kumar et al., 2025; Varouchas, 2026), ethical principles (Rana et al., 2024), ethical governance (Alves et al., 2026), and ethical dilemmas (Singh et al., 2024; Zada et al., 2024). None of the fourteen extracted findings lists energy, carbon, or water as a determinant.

The word "environmental" appears as a factor group in four studies (Agrawal, 2023; Alcalá et al., 2025; Mercuri et al., 2025; Yuan et al., 2025) and as environmental dynamism, a moderator, in one (Singh et al., 2024). One title names environmental, social, and governance considerations (Zada et al., 2024), but the extracted finding concerns innovation, performance, and ethical dilemmas. In the clinical and translational network, the primary concerns were data security, lack of clinician trust, and AI bias (Idnay et al., 2024).

4.3 Group B: environmental performance as outcome

The eleven studies report environmental or sustainability gains linked to GenAI or AI: improved environmental performance through ESG sensemaking (Bag et al., 2026); improved market and sustainability performance (Joshi et al., 2026); improved circular and sustainable supply chain performance (Malhotra & Manzoor, 2025); better decision quality and efficiency in sustainable supply chains (Liu et al., 2026); enablers of green and responsible supply chains (Jamwal et al., 2026); green innovation and knowledge exchange (Liccardo et al., 2025); higher perceived sustainability of platforms with lean themes (Singh et al., 2026); improved financial and environmental performance through AI-driven green process innovation (Liu et al., 2025); reduced ecological footprints and carbon emissions (Wang et al., 2024); potential in environmental assessment (Rahman et al., 2026); and indirect effects on eco-conscious behavior (Laachach & Sadiku-Dushi, 2026).

Several of these studies report moderating conditions. Regulatory uncertainty amplifies the effect on environmental performance, while excessive sustainability-related information weakens it (Bag et al., 2026). Regulatory governance and ethical factor shape performance in sustainable supply chains (Liu et al., 2026). Climate change intentions amplify the behavioral effects (Laachach & Sadiku-Dushi, 2026).

Two findings carry qualifications: higher technology readiness may not enhance supply chain efficiency (Malhotra & Manzoor, 2025), and environmental assessment requires hybrid modeling, participatory data governance, and sustainable AI infrastructures (Rahman et al., 2026). One title names carbon footprint challenges (Laachach & Sadiku-Dushi, 2026), yet the extracted finding concerns behavioral mediation. None of the eleven extracted findings quantify the footprint of the GenAI tool itself.

4.4 Group C: environmental burden

Eight of the eleven findings describe the burden as substantial, significant, hidden, or high (Berthelot et al., 2025; Bozkurt, 2025; Desroches et al., 2025; Esho et al., 2026; Ligozat et al., 2022; Oliveira et al., 2026; Ruggeri et al., 2025; Xiao et al., 2025). One describes it as small (Sidorkin, 2025). Two identify determinants of the footprint without a directional judgement in the extracted finding (d'Orgeval et al., 2026; Friday & Ali, 2024).

The findings name the following sources of burden and variation: energy, water, and material consumption (Bozkurt, 2025); energy demand and rare materials (Esho et al., 2026); user terminals and networks (Berthelot et al., 2025); data center design, model choice, geographic location, and grid carbon intensity (d'Orgeval et al., 2026); and the scale of model training (Ruggeri et al., 2025). Magnitude claims to include up to 4,600 times more energy for large generative models than for traditional ones (Desroches et al., 2025). Three findings point beyond technical fixes: decarbonizing electricity does not solve the sustainability issues of GenAI

services (Berthelot et al., 2025), AI's impacts require system-level governance (Oliveira et al., 2026), and net-zero goals require coordination across the AI value chain (Desroches et al., 2025).

4.5 Group D: instruments and governance

Table 2 lists the criteria and instruments proposed across Groups C and D.

Table 2: Criteria and instruments proposed in the corpus

Instrument or criterion	What it addresses	Source
Full-cost accounting	Energy, water, and material consumption	Bozkurt (2025)
Sustainability index	Balance between efficiency and resources spent under high-volume queries	Antoniuk & Koliada (2025)
Standardized measurement protocols	Carbon accounting, including user behavior and lifecycle monitoring	Kim et al. (2026)
Life cycle mapping	Phase-explicit mapping with system levers and calibrated measurement across energy, carbon, water, and embodied impacts	Rojahn & Grum (2026)
Life cycle analysis of data center typologies	Environmental cost per e FLOP; effect of model choice, location, and grid carbon intensity	d'Orgeval et al. (2026)
Green AI benchmarking and certification	Energy-conscious development; certification of energy-efficient models	Malik (2025)
Standardized benchmarks and assessment tools	Green AI in finance: performance, compliance, and environmental sustainability	Elbouknify et al. (2026)
Operational constraints and decision-rule prompts, with human-in-the-loop governance	Carbon footprint of GenAI in economic research workflows	Alonso-Robisco et al. (2026)
Model optimization and efficient algorithms	Balance of performance and resource efficiency	Tabbakh et al. (2024)
Integration into corporate strategy	Digital sustainability, ethical AI governance, and environmental responsibility	Wicaksono & Riharjo (2025)
System-level governance and value-chain coordination	Energy and carbon constraints in design and operational decisions; net-zero goals	Oliveira et al. (2026), Desroches et al. (2025)
Green AI practices	Resource-efficient AI; research ready for industrial implementation; high-quality research without costly cloud servers	Bolón-Canedo et al. (2024), Verdecchia et al. (2023)

Note. Source: authors' elaboration based on the ten studies classified under Group D (instruments and governance).

Six of the twenty-one studies in Groups C and D connect the burden to an organizational decision: Alonso-Robisco et al. (2026), Antoniuk & Koliada (2025), Bozkurt (2025), Elbouknify et al. (2026), Oliveira et al. (2026), and Wicaksono & Riharjo (2025). The other fifteen address aggregate impact, infrastructure, model development, or measurement.

4.6 The proposition against the three patterns

Table 3 reports the outcome of the three checks defined in Section 3.4.

Table 3: Evidence relative to the working proposition

Pattern	Result
(1) Ecological cost among determinants in adoption studies	0 of 14 extracted findings; an ethical construct appears in 6 of 14
(2) Environment as outcome versus cost	Eleven studies report environmental gains as outcomes; none of the eleven quantifies the footprint of the tool
(3) Burden and instrument studies connected to organizational decisions	6 of 21

Note. Source: authors' elaboration based on Tables 1 and 2 and the coding procedure described in Section 3.4.

V. DISCUSSION

5.1 What evidence says about the research question

The corpus does not show organizations building environmental criteria into GenAI adoption decisions. It shows three other things. Adoption studies explain uptake with organizational, institutional, and ethical variables, and none of the fourteen extracted findings place the footprint of the technology among them. Sustainability studies treat the environment as something GenAI delivers. Footprint and instrument studies describe what could be measured and governed, and only six of twenty-one link that to an organizational decision. The answer to the research question is therefore conditional.

Where the evidence does describe environmental criteria entering organizational practice, it points to ESG sensemaking (Bag et al., 2026), operational constraints paired with human oversight (Alonso-Robisco et al., 2026), and a sustainability index (Antoniuk & Koliada, 2025). Each of the three rests on a single study in this corpus.

The proposition holds in the sense the evidence can test. Readiness, competitive pressure, innovation, and performance carry the adoption studies. The qualification matters, though. The corpus measures the literature's vocabulary, not organizational conduct. An adoption model that omits ecological cost may reflect its builders' choices, and firms may weigh footprints informally without any study recording it. The reviewed evidence tests neither possibility.

5.2 Why the environment enters as outcome and not as cost

The pattern has several plausible mechanisms. The evidence supports each only in part, and we present them as interpretation.

The architecture of the models themselves is one candidate. Determinant structures reserve the "environmental" slot for context. In Vietnam's banking sector that context is competitive pressure and government support (Ajili et al., 2025), and other studies sort determinants into technological, organizational, and environmental groups (Agrawal, 2023; Alcalá et al., 2025; Yuan et al., 2025). Ecological cost has no construct to enter, and researchers who adopt the structure inherit the omission.

Benefit-side framing sits comfortably beside a productivity narrative. An organization can adopt GenAI for performance and later report sustainability gains (Bag et al., 2026; Joshi et al., 2026; Malhotra & Manzoor, 2025). Neither story contains a visible tradeoff. The corpus also warns that AI built for environmental purposes may carry hidden negative impacts, including increased greenhouse gas emissions (Ligozat et al., 2022), and none of the eleven outcome studies quantifies the footprint of the tool. An outcome-only account can therefore look green while leaving the cost uncounted.

Distance also plays a role. Between an organization's decision and the resulting footprint stand actors the organization does not control: the data center design, its location, and the carbon intensity of its grid (d'Orgeval et al., 2026; Xiao et al., 2025), and the terminals and networks that carry the service (Berthelot et al., 2025). The buyer sees a service, not a data center. Costs stay hidden (Bozkurt, 2025), accounting practice remains immature (Kim et al., 2026), and the authors who study the problem call for coordination across the value chain (Desroches et al., 2025) and for system-level governance (Oliveira et al., 2026). When no single actor owns the number, no single actor has reason to ask for it.

Disagreement over size compounds the problem. Sidorkin (2025) reports a small footprint, while others report sector-scale impacts (Desroches et al., 2025; Ruggeri et al., 2025). Because the studies count different objects, the disagreement need not be a contradiction. For a decision-maker it is still a reason to defer. The contested cost is easy to discount.

Information itself may matter too. Excessive sustainability-related information weakens the positive effect of GenAI integration on environmental performance (Bag et al., 2026). Adding metrics, in other words, does not automatically improve decisions. The single sustainability index proposed by Antoniuk and Koliada (2025) and the standardized protocols requested by Kim et al. (2026) point toward parsimony.

5.3 Ethics as a template

Ethics offers a useful comparison. Ethical leadership, principles, governance, and dilemmas became stable constructs in adoption models (Alves et al., 2026; Kumar et al., 2025; Rana et al., 2024; Singh et al., 2024; Varouchas, 2026; Zada et al., 2024). Rana et al. (2024) show that institutional pressures and ethical principles drive adoption, which suggests that the institutional channel is one route through which ethics reached adoption.

Environmental criteria could travel the same route. The corpus already contains signs that regulatory conditions shape the environmental effects of GenAI: regulatory uncertainty amplifies the effect on environmental performance (Bag et al., 2026), regulatory governance influences performance in sustainable supply chains (Liu et al., 2026), and government and policy support enable green adoption (Jamwal et al., 2026).

Proposals for certification (Malik, 2025), public action (Goff, 2024), and ecosystem-wide approaches (Helms et al., 2025) point in the same direction. Wicaksono and Riharjo (2025) go one step further and treat ethical AI governance and environmental responsibility as parts of one corporate strategy. No study in the corpus tests whether institutional pressure carries environmental standards into adoption decisions. We offer this as an inference to be evaluated, not a finding.

5.4 Theoretical implications

The review suggests two revisions to adoption theory.

One revision splits "environmental" into two constructs. The contextual environment (competition, regulation, government support) and the ecological cost of the technology (energy, water, carbon, materials) answer different questions, and literature uses one word for both. Adoption models need the second as a separate antecedent. It is testable: does perceived or measured footprint predict intention, usage intensity, or model choice?

The other distinguishes three positions for sustainability in a model: as a criterion applied before adoption, as an outcome reported after it, and as a constraint that governs use. Group B places sustainability almost entirely in the second position. Because GenAI can be both an environmental instrument and an environmental burden (Ligozat et al., 2022; Wang et al., 2024), a model that records only outcomes can overstate net benefit. The finding that too much sustainability information reduces the effect (Bag et al., 2026) adds a further complication: the relation between environmental information and outcomes may not be linear, and models should allow for a threshold.

5.5 Practical implications

Five implications follow; each anchored in the instruments of Table 2.

- 1) Adopters can put the footprint on the evaluation checklist. The corpus offers a compact set of candidates: energy, carbon, water, and material consumption (Bozkurt, 2025; Rojahn & Grum, 2026), plus data center location and grid carbon intensity, model choice (d'Orgeval et al., 2026), query volume (Antoniuk & Koliada, 2025), and the terminals and networks on the user side (Berthelot et al., 2025).
- 2) Location and model choice are levers that adopters can ask about, since both influence the footprint (d'Orgeval et al., 2026).
- 3) Operating rules can reduce the footprint after adoption. Operational constraints and decision-rule prompts can reduce the carbon footprint of GenAI in economic research workflows, with human-in-the-loop governance ensuring productivity and environmental efficiency (Alonso-Robisco et al., 2026).
- 4) Comparability depends on standardized protocols and benchmarks (Elbouknify et al., 2026; Kim et al., 2026; Malik, 2025). Without them, adopters have no common basis for comparing figures across sources.
- 5) A small number of indicators is preferable to a large dashboard, given the evidence that excess sustainability information weakens the gains (Bag et al., 2026) and the case for a single index (Antoniuk & Koliada, 2025).

At the policy level, the corpus adds that decarbonizing electricity alone will not suffice (Berthelot et al., 2025) and that action across the value chain (Desroches et al., 2025) and public action (Goff, 2024) both matter.

VI. CONCLUSION

6.1 Contributions

This review makes three contributions. It reads two literatures that rarely meet, and it shows that the environment reaches adoption research in four roles: contextual factors, performance outcome, burden to be measured, and object to be governed. It tests the proposition against the extracted evidence and finds it supported in the literature: no adoption study among the fourteen extracted findings records ecological cost as a determinant, 11 studies treat environmental performance as an outcome, and six of 21 burden and instrument studies connect to organizational decisions. And it offers conceptual repair and a working set of candidate criteria: separating the contextual environment from ecological cost and assembling the instruments that could turn cost into a decision criterion.

6.2 Limitations

Several limits follow from the design. The review extracted one main finding per study, so a determinant that the extracted finding omits may still appear in the full text. The results on absence are therefore claims about the extracted findings and call for full-text verification. The search relied on a single TITLE-ABS-KEY query with three concept blocks; studies that treat environmental criteria without using these terms fall outside it. The corpus mixes journal articles, conference papers, and preprints, and no formal appraisal of quality is reported here.

Contexts range from banking to clinical research to supply chains, and national context can change results (Mercuri et al., 2025), which rules out pooling and limits generalization. Thirteen sources carry no extracted finding and contribute only through their stated scope. Assignment to groups rests on the primary focus of each finding, and several studies straddle groups. Forty-five of the fifty-nine sources appeared in 2025 or 2026, and headline figures such as the 4,600-fold energy difference (Desroches et al., 2025) and the small-footprint estimate (Sidorkin, 2025) each come from one study.

Finally, the test of the proposition relies on absence in literature, which cannot separate what organizations do not do from what researchers have not measured.

6.3 Future research

Six lines of work follow directly from the gaps identified.

1. Field studies of adoption decisions, through cases or surveys, that record whether footprint data are requested, who holds them, and what weight they receive.

2. Adoption models that add ecological cost as a separate antecedent and evaluate its effect on intention, usage intensity, and model choice.
3. Tests of whether institutional pressure carries environmental standards into adoption, comparing regulatory settings (Bag et al., 2026; Jamwal et al., 2026; Liu et al., 2026).
4. Experiments on how much sustainability information to present, contrasting a single index (Antoniuk & Koliada, 2025) with multi-metric displays, considering the threshold suggested by Bag et al. (2026).
5. Reconciliation of footprint estimates under common accounting boundaries (Kim et al., 2026; Rojahn & Grum, 2026), together with tests of whether the disagreement between small and sector-scale estimates changes managerial decisions.
6. Sector comparisons across banking, insurance, the public sector, manufacturing, clinical research, and supply chains, where national context is known to matter (Mercuri et al., 2025).

VII. DISCLOSURE

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