

## Ethical issues at the intersection of artificial intelligence and sustainability: A systematic review and its implications for science, mathematics, and technology education

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### Abstract

Artificial intelligence (AI) is increasingly presented as a tool for sustainable development, yet the ethical costs of this role remain scattered across separate bodies of literature. This systematic review aims to identify the ethical issues arising at the intersection of AI, ethics, and sustainability. Following the preferred reporting items for systematic reviews and meta-analyses 2020 statement, Scopus and Web of Science were searched in February 2026, yielding 5,794 records. Screening, eligibility assessment and quality appraisal were carried out by two researchers, and 74 studies were included. Verbatim passages addressing the intersection were extracted from each study and examined using a hybrid thematic approach, resulting in 921 coded passages. Five themes were identified: algorithmic bias and unequal AI outcomes; privacy, surveillance, and human autonomy; transparency, accountability, and epistemic integrity; AI governance and corporate responsibility; and the ecological ethics of AI systems. Concerns regarding transparency and accountability accounted for the largest share of passages (30.9%), while ecological concerns were voiced across all five themes rather than in a separate discussion. The themes were mapped onto the environmental, social, and governance dimensions of sustainability and onto the United Nations sustainable development goals. Transparency and accountability thus emerge as a structural prerequisite rather than a procedural add-on for sustainable AI. Educational research is markedly underrepresented at this intersection (5 of 74 studies); the implications of the five themes for science, mathematics, and technology education are therefore developed in detail, from carbon- and water-footprint modelling tasks to data-justice and AI-literacy work in the classroom.

**Keywords:** artificial intelligence, ethics, sustainability, systematic review, algorithmic bias, sustainable development goals, AI literacy, STEM education

## INTRODUCTION

The relationship between artificial intelligence (AI) and sustainability is bidirectional. While AI technologies offer powerful tools for solving complex problems such

as climate, energy, and resource management, they also generate new environmental and social costs through the ways they are developed and used (Nishant et al., 2020). A large-scale expert assessment found that AI could support the achievement of 134 of the 169 targets under the sustainable development goals (SDGs).

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### Contribution to the literature

- Existing reviews treat AI and sustainability from an application or technical angle, and ethics stays secondary. This study offers the first systematic synthesis that places ethical issues at the center.
- Five themes and thirteen categories were derived from 921 verbatim passages across 74 studies. The themes were mapped onto the environmental, social, and governance dimensions and onto the SDGs. The findings show that transparency and accountability are a structural prerequisite for sustainable AI, while ecological concerns run through all themes.
- Only 5 of the 74 studies are set in education, and none addresses science or mathematics education. The study develops the implications of the five themes for STEM education and offers a framework for future research in this area.

Conversely, the same assessment also determined that it could hinder 59 of these targets (Vinuesa et al., 2020). Therefore, it is not surprising that the literature treats AI as both a solution and a source of problems in terms of sustainability.

It is clear that this dual nature carries an ethical dimension. The use of technology for sustainability purposes raises questions about who will benefit, who will bear the costs, and what will be passed on to future generations (van Wynsberghe, 2021). Galaz et al. (2021) demonstrate that AI applications in sectors critical to sustainability carry systemic risks ranging from algorithmic bias to cascading system failures. Nordgren (2023) notes that the relationship between AI and climate change involves a dual role from both ethical and technical perspectives. However, this relationship has received limited attention from an ethical perspective. This study is situated at the intersection of three fundamental concepts: AI, ethics, and sustainability. While each pair of concepts has its own well-established body of literature, the area where the three intersect is relatively new, and its theoretical foundations are still being developed.

Existing reviews in the literature cover this intersection only partially. Application-focused reviews systematically examine AI's contribution to the SDGs but treat ethical issues as a secondary topic (Kulkov et al., 2024; Toderas, 2025). Technical-focused reviews, by contrast, concentrate on energy efficiency and emissions reduction under the banner of "green AI," largely leaving the normative dimension of the issue out of scope (Bolón-Canedo et al., 2024). Ethics-focused studies mostly consist of individual contributions of a conceptual and philosophical nature (Bossert & Hagendorff, 2023; Heilinger et al., 2024). These contributions are scattered across the fields of computer science, ethics, and sustainability science. Indeed, it has been reported that comprehensive frameworks for identifying and assessing the environmental and social costs of AI are overlooked even in the policy arena (Bolte et al., 2022). In the available literature, no review has been found that addresses the ethical issues accompanying the use of AI for sustainability as a primary focus and systematically synthesizes them.

Answers to questions such as which ethical issues are concentrated in which dimensions of sustainability, which theoretical frameworks are used to address these issues, and which solutions have been proposed are scattered throughout the literature.

This systematic review is an effort to address this gap. The aim of this study is to systematically identify, classify, and synthesize the ethical issues related to the use of AI for sustainability. In this regard, the study seeks to answer three research questions:

- (1) In studies addressing the use of AI for sustainability, which ethical issue themes and subcategories are addressed, and how frequently are they represented in the literature?
- (2) How are these themes distributed across the environmental, social, and governance dimensions of sustainability, and how do they align with the SDGs?
- (3) What governance mechanisms, regulatory tools, and proposed solutions are being developed in the literature to mitigate these issues?

In the following section, the binary intersections of the three core concepts are first briefly addressed, and then the conceptual framework of this review is established by examining the clusters of ethical issues at the intersection of all three.

## CONCEPTUAL FRAMEWORK: FROM BINARY INTERSECTIONS TO A TRIPARTITE INTERSECTION

### The Intersection of AI and Ethics

AI ethics is a field that addresses the normative principles guiding the development and use of the technology. A total of 84 ethical guidelines published by public institutions, companies, and academic organizations were examined. This study identified a global convergence around five principles: transparency, justice and fairness, non-maleficence, accountability, and privacy. However, a clear divergence was observed regarding how these principles should be interpreted and applied (Jobin et al., 2019). In his assessment comparing 22 guidelines, Hagendorff (2020)

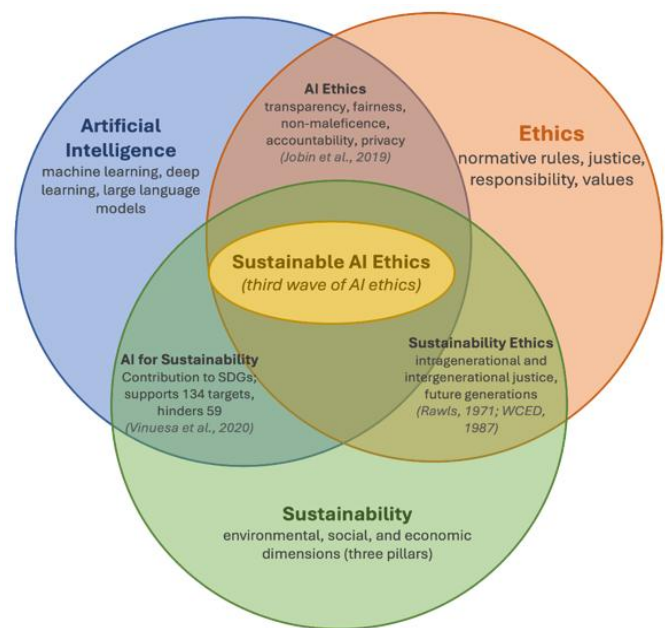
also reports that these principles are reflected only to a limited extent in research and development practices. In contrast, Mittelstadt (2019) argues that a principled approach similar to that in medical ethics cannot achieve the same success in the field of AI. According to him, this field lacks shared goals, professional norms, and accountability mechanisms. It can be said that environmental concerns remained largely invisible in these first-generation guidelines, and sustainability only came to the forefront in subsequent discussions (van Wynsberghe, 2021).

### The Intersection of Ethics and Sustainability

The concept of sustainability itself is grounded in a normative framework. The Brundtland report defined sustainable development as development that meets the needs of the present without compromising the ability of future generations to meet their own needs (WCED, 1987). Langhelle (1999) notes that behind this definition lies a broad normative framework encompassing intragenerational and intergenerational social justice as well as respect for ecological limits. However, in the literature, the dimension of economic growth has overshadowed this framework. On a philosophical level, Barry (1997) grounds sustainability as a requirement of intergenerational justice and emphasizes that the current generation has inherited the planet as a temporary steward. Spijkers (2018), in turn, examines the connection between the SDGs and the principle of intergenerational justice. According to him, the goals' short-term horizon of fifteen years may prove insufficient to safeguard the interests of future generations. These discussions demonstrate that sustainability is, first and foremost, a matter of justice rather than merely a technical list of objectives.

### The Intersection of AI and Sustainability

The third intersection also forms the starting point for a fundamental conceptual distinction in the literature. van Wynsberghe (2021) distinguishes between AI for sustainability and the sustainability of AI. He defines sustainable AI as a movement that upholds ecological integrity and social justice throughout the entire life cycle, from idea generation to education and governance. Dhiman et al. (2024), who adopted a similar classification, systematically reviewed the literature under these two headings and identified a shift toward holistic approaches, accompanied by a marked increase in the number of publications after 2019. Earlier, Khakurel et al. (2018) analyzed the impacts of AI through the five dimensions of sustainability and demonstrated that negative impacts, as well as positive ones, were observed across all dimensions. The distribution of AI's positive and negative effects on objectives was visualized by Vinuesa et al. (2020).



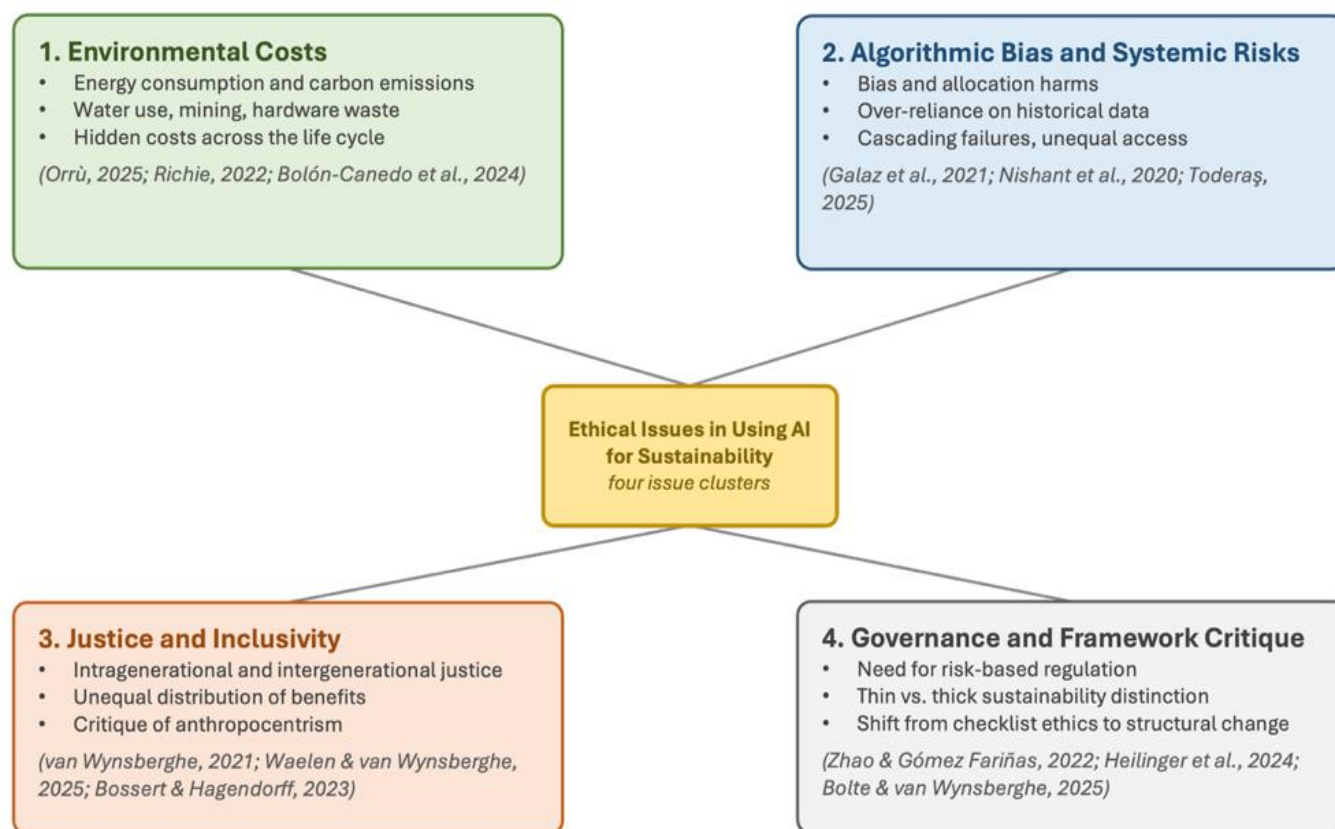
**Figure 1.** The binary intersections and the tripartite intersection area of the concepts of AI, ethics, and sustainability (created by the authors based on literature)

### The Triple Intersection: Ethics of Sustainable AI

Each of these two perspectives, taken on its own, presents an incomplete picture. While AI ethics guidelines tend to relatively neglect environmental costs (van Wynsberghe, 2021), studies focusing on AI applications for sustainability also often overlook the technology's own ethical and ecological costs (Heilinger et al., 2024). The intersection of these three concepts, however, opens up a field that has the potential to address both of these shortcomings simultaneously. Bolte and van Wynsberghe (2025) position sustainable AI as the third wave of AI ethics. This approach is based on a structural shift that addresses ethical issues not at the level of individual applications but at the level of power structures and systems. Heilinger et al. (2024) argue that only a comprehensive assessment that considers both environmental and social impacts and costs can justify a sound sustainability judgment. The binary intersections of the three concepts and the central tripartite intersection area are presented in **Figure 1**.

### ETHICAL ISSUE CLUSTERS AT THE TRIPARTITE INTERSECTION

A review of the literature reveals that the ethical issues in the tripartite intersection can be grouped into four clusters: environmental costs, algorithmic bias and systemic risks, justice and inclusivity, and governance and framework criticism. These clusters and their supporting evidence from the literature are summarized in the concept map in **Figure 2**. These clusters are derived from the conceptual literature and serve as the a priori starting point of the analysis. The themes reported in the findings are the outcome of coding the corpus, and



**Figure 2.** Concept map of the a priori clusters of ethical issues derived from the conceptual literature on the use of AI for sustainability (created by the authors based on literature)

they are therefore not expected to map onto the clusters one to one.

### Environmental Costs

The first cluster of ethical issues centers on the environmental costs of AI. The training and inference processes of large models generate high energy consumption and carbon emissions. When the extraction of rare earth elements, water consumption, and hardware waste are factored in, these costs extend across the entire life cycle (Orrù, 2026). In the context of healthcare, Richie (2022) argues that the primary focus in AI ethics should be on the technology's environmental impact rather than software flaws. Accordingly, he proposes an evaluation based on criteria of health, justice, and resource conservation. In contrast, the green AI approach demonstrates that these costs can be reduced through energy-efficient algorithms and emission measurement tools (Bolón-Canedo et al., 2024). However, the lack of established measurement standards means that environmental costs remain largely invisible, making accountability difficult (Ligozat et al., 2022).

### Algorithmic Bias and Systemic Risks

The second set of issues concerns algorithmic bias and systemic risks. Bias of this kind is rarely a single defect; it is distributed across the stages of a system. It

originates in the data, where historical records carry the inequalities of the settings that produced them. It is then consolidated in the model, where optimization for aggregate accuracy can conceal uneven performance across groups. It becomes consequential at the point of deployment, where an output is turned into a decision about people or places. Galaz et al. (2021) examined sectors critical to sustainability, such as agriculture, forestry, and marine resources. This study identifies three systemic risks: algorithmic bias and allocation failures, the unequal distribution of access and benefits, and cascading system failures. What distinguishes these risks in a sustainability context is their spatial character. The data on which environmental models depend are themselves unevenly produced, since sensor networks, satellite coverage, and monitoring infrastructures are denser in wealthier regions. The places least represented in the data are therefore often those most exposed to environmental harm (McGovern et al., 2022). Nishant et al. (2020), meanwhile, list the overreliance of machine learning models on historical data, the uncertainty in human behavioral responses, and the difficulty in measuring the effects of interventions among the field's fundamental challenges. A further consideration is that bias in this domain is seldom visible to those affected by it. An allocation of resources, a risk score, or a climate projection reaches a community as a technical result rather than as a contestable decision, which weakens the accountability mechanisms discussed below. In a recent

**Table 1.** Search strategy and identification of records

| Parameter               | Detail                                                                                                                                                                                                                                                                              |
|-------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Databases               | Scopus; WoS (core collection)                                                                                                                                                                                                                                                       |
| Search date             | February 2026                                                                                                                                                                                                                                                                       |
| Fields searched         | Title, abstract, author keywords                                                                                                                                                                                                                                                    |
| Search string           | ("artificial intelligence" OR "machine learning" OR "deep learning") AND ("ethics" OR "ethical" OR "bias" OR "fairness" OR "transparency" OR "accountability") AND ("sustainability" OR "sustainable development" OR "Sustainable Development Goals" OR "green" OR "environmental") |
| Records identified      | Scopus n = 2,906; WoS n = 2,888; total n = 5,794                                                                                                                                                                                                                                    |
| Duplicates removed      | n = 1,782                                                                                                                                                                                                                                                                           |
| Unique records screened | n = 4,012                                                                                                                                                                                                                                                                           |

systematic review, these risks were integrated into a risk matrix linking socioeconomic, ecological, and algorithmic dimensions (Toderas, 2025). Hence, it can be said that bias is not merely a technical flaw but a structural problem that threatens sustainability goals themselves.

### Justice and Inclusion

The third set of issues revolves around the axis of justice and inclusivity. The principles of intragenerational and intergenerational justice take on concrete meaning at this triple intersection. van Wynsberghe (2021) places the tension between innovation and the equitable distribution of resources, as well as intragenerational and intergenerational justice, at the center of sustainable AI. Waelen and van Wynsberghe (2025) also criticize the narrowing of the discussion to its environmental dimension and demonstrate that the environmental costs of AI are often intertwined with social and economic issues. From the field of management education, Goralski and Tan (2020) draw attention to the likelihood that the benefits of technology will be concentrated among already privileged groups. However, Bossert and Hagendorff (2023) argue that current approaches to sustainable AI remain human-centered. The authors propose expanding theories of intergenerational justice to include sentient animals. It can be said that this debate over the scope of justice has not yet been resolved, and the normative foundations of the field remain open to discussion.

### Critique of Governance and Frameworks

The fourth set of issues concerns the adequacy of governance and ethical frameworks. Zhao and Gómez Fariñas (2023) argue that unregulated AI poses a threat to sustainability and propose a risk-based, harmonized regulatory framework. Nordgren (2023) presents an ethical analysis that distinguishes between companies' emission reduction responsibilities and governments' oversight responsibilities, specifically in the context of climate change. On the other hand, the frameworks themselves are also subject to criticism. Doubts regarding the principled approach (Mittelstadt, 2019) resonate in this context as well. Heilinger et al. (2024)

warn against the use of the concept of sustainability as a mere label through one-dimensional assessments. Similarly, Bolte et al. (2022) characterize the approach based on existing lists of principles as "checklist ethics" and recommend a shift toward "desirability ethics." The common thread among these critiques is the questioning of the practical implementation of principles rather than their mere existence.

## METHOD

### Research Design

This study was designed as a systematic review to analyze the literature at the intersection of AI ethics and sustainability concepts. The preferred reporting items for systematic reviews and meta-analyses 2000 (PRISMA 2000) guidelines were followed in planning and reporting the process, and the completed checklist, showing where each item is reported, is provided as [Supplementary File 1](#) (PRISMA checklist). The analysis used verbatim statements from primary sources as coding units, rather than adding a secondary layer of interpretation.

### Databases and Search Strategy

The literature search was conducted in February 2026 in the Scopus and Web of Science (WoS) core collection databases. The search string was created by combining three conceptual clusters using Boolean operators: AI, ethics, and sustainability. The full search string and search results are presented in [Table 1](#). The search was performed on the title, abstract, and keywords fields; 2,906 records were retrieved from Scopus and 2,888 from WoS. Thus, a total of 5,794 records were identified from the two databases.

### Eligibility Criteria

The inclusion criteria were defined as follows:

- studies addressing the intersection of AI, machine learning, or deep learning ethics with the concept of sustainability,
- studies published in peer-reviewed journals in English, and

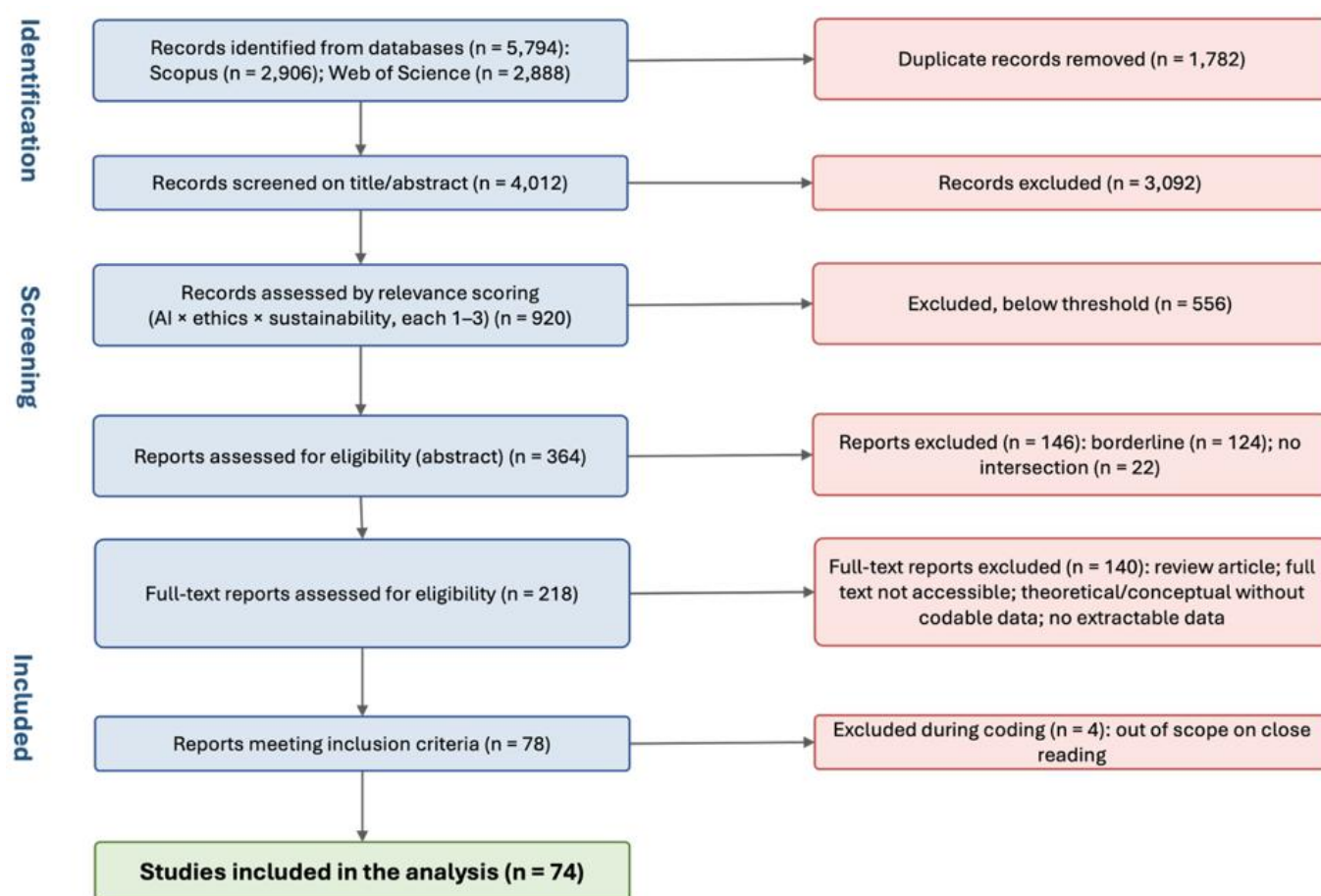


Figure 3. PRISMA 2020 flow of study selection and analysis (created by the authors)

(c) studies for which the full text is accessible.

The exclusion criteria are as follows: studies that address only AI ethics or only sustainability without addressing the intersection of the two; records for which the full text is unavailable; and documents such as letters to the editor, conference abstracts, and similar materials that do not constitute full-fledged research.

### Selection of Studies

The 4,012 unique records were screened at the title and abstract level. Records clearly unrelated to the topic were removed, and the remaining 920 records underwent a structured eligibility scoring procedure in which each record was rated from 1 to 3 on each of three dimensions: AI, ethics, and sustainability. A rating of 1 indicated that the dimension was absent or incidental, 2 that it was present but peripheral, and 3 that it was an explicit focus of the record. A rating of at least 2 on all three dimensions was a necessary condition for retention, and the 320 records rated 1 on any dimension were excluded on that basis alone. The records meeting this condition were then assessed qualitatively against the eligibility criteria, and a further 159 were excluded with a documented reason recorded for each; the most frequent reason was that the AI-ethics dimension was technical or incidental rather than substantive. Forty-one of these decisions were marked as requiring discussion

and were resolved jointly by the two researchers. A further 72 records were set aside at this stage as review-type studies, in line with the exclusion criteria. This procedure yielded 364 records, which underwent a second, independent abstract-level assessment and were classified as suitable ( $n = 218$ ), borderline ( $n = 124$ ), or unsuitable ( $n = 22$ ). Full texts were retrieved for the 218 records classified as suitable; the borderline records were not advanced to full-text review, and this decision is acknowledged as a limitation. At the full-text stage, review-type studies, records whose full text was unavailable, and reports that yielded no extractable passages on the intersection were excluded; 140 reports were eliminated, leaving 78 studies. Four further studies were excluded during quality appraisal and close reading: three because they were themselves review-type publications and one because its topical relevance proved insufficient. Thus 74 studies entered the analysis. Screening and eligibility assessment were carried out by two researchers, and disagreements were resolved by discussion. All stages of the selection process and the number of records obtained at each stage are presented in the PRISMA flowchart in Figure 3. The characteristics of the 74 included studies, including design, appraisal score, number of coded passages and themes covered, are reported in [Supplementary File 2](#) (quality appraisal).

**Table 2.** Quality appraisal instruments and outcomes for the 74 included studies

| Instrument (criteria)            | Study design                | n  | MS    | Range   | LR | MR | HR |
|----------------------------------|-----------------------------|----|-------|---------|----|----|----|
| Conceptual-paper rubric (6)      | Conceptual/theoretical      | 36 | 72.6% | 42-92%  | 19 | 17 | 0  |
| Framework-development rubric (6) | Framework/model development | 14 | 91.1% | 67-100% | 13 | 1  | 0  |
| JBIC, adapted (7)                | Quantitative                | 12 | 82.7% | 57-100% | 8  | 4  | 0  |
| CASP, adapted (6)                | Qualitative                 | 10 | 74.9% | 50-100% | 6  | 4  | 0  |
| MMAT, adapted (5)                | Mixed methods               | 1  | 80.0% | -       | 1  | 0  | 0  |
| CASP case study (5)              | Case study                  | 1  | 50.0% | -       | 0  | 1  | 0  |
| Total                            |                             | 74 | 77.9% | 42-100% | 47 | 27 | 0  |

Note. MS: Mean score; LR: Low risk; MR: medium risk; HR: High risk; Scores are percentages of the instrument maximum and are reported from the full-text appraisal round, which was taken as definitive; Studies scoring below 40% were classified as high risk and excluded; no study fell below this threshold; Three review-type reports and one study with insufficient topical relevance were excluded at this stage and are not included

## Quality Appraisal

The methodological quality of all 78 full-text reports was appraised with instruments matched to study design. Quantitative studies ( $n = 12$ ) were appraised with an adapted JBI critical appraisal checklist (7 criteria) and qualitative studies ( $n = 10$ ) with an adapted CASP checklist (6 criteria). The single mixed-methods study was appraised with an adapted MMAT (5 criteria), the single case study with the CASP case-study checklist (5 criteria), and review-type reports with an AMSTAR/PRISMA-based checklist (6 criteria). Because a substantial part of the corpus consists of conceptual and framework-development work for which no standard instrument exists, two purpose-built six-criterion rubrics were used, one for conceptual papers ( $n = 36$ ) and one for framework-development studies ( $n = 14$ ). The conceptual-paper rubric assessed theoretical grounding, argumentative consistency, clarity of the ethical problem, the explicitness of the sustainability link, originality of contribution, and acknowledgement of limitations. The framework-development rubric assessed the literature base, the development process, validation, the ethical dimension, practical implications, and limitations. Each criterion was scored 0, 0.5, or 1, and the total was expressed as a percentage of the instrument maximum. Reports scoring below 40% were classified as high risk and excluded on quality grounds; no report fell below this threshold. Scores between 40% and 69% were classified as medium risk and retained, with the quality profile reported rather than used as a weighting factor. The appraisal was conducted independently by two researchers, once on the basis of the bibliographic record and abstract and once on the basis of the full text. The full-text round was taken as definitive and is the round reported in **Table 2**. The agreement between the two rounds is reported in the validity and reliability subsection. study-level and criterion-level scores for every instrument, together with the passage in the full text on which each score was based, are provided in **Supplementary File 3** (study characteristics).

## Data Extraction

From each included study, only direct passages addressing the intersection of AI ethics and

sustainability were extracted; no commentary or inferences were added to the passages. The full text of every included study was read in its entirety before extraction, and passages were identified during that reading rather than through keyword retrieval. The scope of the data extraction varies depending on the study type. Abstracts were excluded from all studies because they duplicated the main text. In empirical and IMRaD-structured studies, the introduction and literature review sections were excluded; the methods, results, discussion, and conclusions sections, along with topic-specific sections, were reviewed. In conceptual studies, however, sections that advance the argument were included, while passages that merely summarized other authors were excluded. The analysis was conducted in two stages. In the first stage, exact-match passages related to the overlap were collected; in the second stage, passages that did not contain the focus author's own conclusions but merely cited another publication were excluded. At the end of this process, 921 overlapping passages remained for analysis. Each passage was linked to its source, page, and chapter. Passages were distributed evenly across the corpus rather than concentrated in a few long publications: each study contributed between 5 and 20 passages (mean = 12.6, median = 12, inter-quartile range = 10-16), and the five studies contributing most accounted for 10.2% of all passages. Conceptual and framework-development studies contributed 670 passages and empirical and case studies 240, consistent with the composition of the corpus (54 conceptual or framework-development studies, 18 empirical or case studies, and 2 studies coded in a final supplementary round).

## Thematic Analysis

A hybrid thematic approach was adopted in the analysis; the four clusters set out in the conceptual framework (**Figure 2**), which were derived from established work on AI ethics and on sustainability ethics, were taken as the a priori starting point, and the coding frame was then expanded with themes emerging from the data. As a result of this process, five main themes and thirteen categories were identified. The unit of coding is the passage; each passage was assigned to one of the thirteen categories, and the categories were

grouped under the five main themes. Most articles contributed to more than one theme. Additionally, the type of study to which the passage belonged (empirical or conceptual) was recorded. The frequencies of the themes and the distributions of articles and article types were analyzed descriptively. The definitions and frequencies of the thematic framework are presented in the findings section.

### Mapping to Sustainability Dimensions and the SDGs

Each of the thirteen categories was assigned to one of the three sustainability dimensions (environmental, social, or governance) on the basis of its definition, and the passage counts were aggregated accordingly. The environmental dimension covers C5.1 (86 passages, 9.3%), the social dimension covers C1.1-C1.3 and C2.1-C2.3 (463 passages, 50.3%), and the governance dimension covers C3.1-C3.3 and C4.1-C4.3 (372 passages, 40.4%). Relevance to the SDGs was recorded at the record level during classification. For each study, the goals addressed in its title, abstract, and keywords were tagged, and the theme-SDG matrix presented was derived by combining these study-level tags with the theme distribution of that study's passages. The values are therefore derived rather than coded directly at passage level, and they should be read as relative weights rather than as exact passage counts.

### Validity and Reliability

The reliability of the review was examined at three levels. First, the exactness of every extracted passage was verified programmatically by substring matching against the normalized text of the source. The completeness and formal consistency of the coding were audited in the same way. It was confirmed that every passage carried exactly one category code and that only the defined categories were used. This audit establishes completeness and formal consistency rather than the validity of individual assignments, and it is reported as such. Second, agreement between the two researchers

was quantified at the appraisal stage. All 74 included studies were classified and appraised twice and independently: by the first researcher on the basis of the bibliographic record and abstract, and by the second researcher on the basis of the full text. Agreement on study-design classification, which determines the appraisal instrument, was 82.4% (Cohen's  $\kappa = 0.744$ ), indicating substantial agreement; the 13 disagreements were resolved in favor of the full-text assessment. Agreement on the three-level risk classification was lower (70.3%,  $\kappa = 0.279$ ): with fuller information, the second researcher applied the criteria more strictly and reclassified 14 studies from low to medium risk, which lowered the mean quality score from 83.8% to 77.9%. Because no study fell below the 40% exclusion threshold under either assessment, this divergence affects the reported quality profile rather than the composition of the corpus, and the full-text assessment was taken as definitive; **Table 3** therefore reports the full-text round. Third, at the coding stage the thirteen categories were consolidated from 138 emergent open codes assigned in a prior open-coding round, so that every category assignment remains traceable to the open code from which it derives. In addition, a random sample of 25 passages was independently re-coded with the framework reapplied, and all assignments were confirmed. The full texts of all 74 included studies were read in their entirety before and during coding rather than screened at abstract level, so the category assignments rest on complete readings of the sources. The independent re-code, however, covered 2.7% of the corpus. No coefficient of agreement is therefore reported for passage-level coding, and the predominantly single-coder design of this stage is stated as a limitation.

## FINDINGS

The thematic analysis of 921 intersecting passages extracted from 74 articles yielded five main themes, which are defined with their thirteen categories in **Table 3**. These themes encompass the environmental,

**Table 3.** Thematic taxonomy of ethical issues at the AI/GenAI-sustainability intersection

| Theme                                       | Code | Category                                        | Description                                                                                                            | n   | %    | N  | Example articles                                                                                                                                                                                                                                           |
|---------------------------------------------|------|-------------------------------------------------|------------------------------------------------------------------------------------------------------------------------|-----|------|----|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| T1 – Algorithmic bias & unequal AI outcomes | C1.1 | Algorithmic bias in high-stakes decisions       | Biased AI/ML outputs in high-stakes domains such as criminal justice, hiring, healthcare, and environmental prediction | 105 | 11.4 | 40 | Addison (2026); Bag et al. (2026); Baum and Owe (2023); Bossert and Hagendorff (2023); Ghamisi et al. (2025); Hendawy and Ghaz (2024); Javed and Li (2025); McCormack et al. (2026); Nadeem et al. (2026); van der Ven et al. (2025); Yassen et al. (2025) |
|                                             | C1.2 | Exclusion, marginalization, and social equity   | AI-driven exclusion of vulnerable populations; widening social inequalities                                            | 95  | 10.3 | 46 | Alghamdi et al. (2025); Ali et al. (2025); Kiettikunwong et al. (2025); Mazzi (2025); Nizamani et al. (2026)                                                                                                                                               |
|                                             | C1.3 | Digital divide, Global South, and health equity | Unequal access to the benefits of AI; a disproportionate burden on low-income and Global South populations             | 32  | 3.5  | 21 | Moyano-Fernández et al. (2024)                                                                                                                                                                                                                             |
| T1 subtotal                                 |      |                                                 |                                                                                                                        | 232 | 25.2 | 64 |                                                                                                                                                                                                                                                            |
| T2 – Privacy, surveillance & human autonomy | C2.1 | Privacy violations & data exploitation          | Unauthorized data collection; surveillance; misuse of personal and behavioral data                                     | 120 | 13.0 | 53 | Fundira et al. (2024), Herrera-Vega (2022), Kittipanya-ngam et al. (2025), Leikas et al. (2022), Manning et al. (2022), Marabelli and Davison (2025), Neethirajan (2023), Nguyen et al. (2025),                                                            |

**Table 3 (Continued).**

| Theme                                                      | Code | Category                                       | Description                                                                                           | n   | %    | N   | Example articles                                                                                                                                                                                                                                                                                                                                                                                                                                                                                  |
|------------------------------------------------------------|------|------------------------------------------------|-------------------------------------------------------------------------------------------------------|-----|------|-----|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
|                                                            |      |                                                |                                                                                                       |     |      |     | Onder (2026), Ricaurte (2022), Riedmann-Streitz et al. (2025), Zada et al. (2024), Zhang et al. (2024)                                                                                                                                                                                                                                                                                                                                                                                            |
|                                                            | C2.2 | Human agency, control, and autonomy            | Erosion of human decision-making capacity; over-reliance on AI; preservation of autonomy              | 28  | 3.0  | 21  | Di Chiacchio et al. (2026) <sup>†</sup>                                                                                                                                                                                                                                                                                                                                                                                                                                                           |
|                                                            | C2.3 | Labor displacement & automation ethics         | Job loss, deskilling, and exploitative gig labor practices driven by AI automation                    | 83  | 9.0  | 38  | Fang et al. (2026), Fraisl et al. (2025), Kulkarni et al. (2024), Nizamani et al. (2025), Vann Yaroson et al. (2025)                                                                                                                                                                                                                                                                                                                                                                              |
| T2 subtotal                                                |      |                                                |                                                                                                       | 231 | 25.1 | 65  |                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                   |
| T3 – Transparency, accountability, and epistemic integrity | C3.1 | Explainability & black-box systems             | Opacity of AI decision-making logic; lack of interpretability; XAI requirements                       | 157 | 17.0 | 56  | Amore and Gentili (2026), Anbarasi and Sankar (2025), Apaolaza et al. (2026), Bartmann (2022), Bostrom et al. (2024), Cordeiro et al. (2026), Corsini et al. (2025), Cugurullo and Xu (2025), Dara et al. (2022), Guzmán Rincón et al. (2026), Le Goff (2026), McNealis (2026), Mondal et al. (2025), Ong et al. (2024), Philipo et al. (2025), Rohde et al. (2024), Shaikhon (2025), Simion (2025), Tong and Li (2024), Vargas-Machado and Bedoya (2025), Yu et al. (2026), Zaidan et al. (2026) |
|                                                            | C3.2 | Accountability deficits & moral responsibility | Diffused responsibility; lack of redress mechanisms; corporate opacity                                | 94  | 10.2 | 39  | Abulibdeh et al. (2024), Alexander et al. (2024), Balan (2024), Bourgeois-Gironde (2025), Katirai (2024), Lehuédé (2025), McGovern et al. (2022), Shussett and Dubljević (2025), Tian et al. (2026), Torres-Rivera et al. (2025)                                                                                                                                                                                                                                                                  |
|                                                            | C3.3 | Misinformation, IP & content integrity         | AI-generated disinformation; copyright violations; false attribution; threats to scientific integrity | 34  | 3.7  | 22  | Geiger and Di Lazzaro (2025)                                                                                                                                                                                                                                                                                                                                                                                                                                                                      |
| T3 subtotal                                                |      |                                                |                                                                                                       | 285 | 30.9 | 65  |                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                   |
| T4 – AI governance & corporate responsibility              | C4.1 | Regulatory & governance frameworks             | AI policy development; legislative gaps; international governance architecture                        | 33  | 3.6  | 27  | Baum and Owe (2023) <sup>†</sup>                                                                                                                                                                                                                                                                                                                                                                                                                                                                  |
|                                                            | C4.2 | Greenwashing & ESG accountability              | Corporate misrepresentation of AI's environmental credentials; ESG reporting failures                 | 39  | 4.2  | 14  | Chen et al. (2026), Wang et al. (2025)                                                                                                                                                                                                                                                                                                                                                                                                                                                            |
|                                                            | C4.3 | Participatory & value-aligned AI design        | Inclusive design; multi-stakeholder governance; value-sensitive AI development                        | 15  | 1.6  | 13  | Dara et al. (2022) <sup>†</sup>                                                                                                                                                                                                                                                                                                                                                                                                                                                                   |
| T4 subtotal                                                |      |                                                |                                                                                                       | 87  | 9.4  | 44  |                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                   |
| T5 – Ecological ethics of AI systems                       | C5.1 | Carbon and energy footprint of AI              | Greenhouse gas emissions, electricity consumption, and thermal pollution from AI infrastructure       | 86  | 9.3  | 42  | Bolte et al. (2022), Cina et al. (2025), Di Chiacchio et al. (2026), Melguizo et al. (2026)                                                                                                                                                                                                                                                                                                                                                                                                       |
| T5 subtotal                                                |      |                                                |                                                                                                       | 86  | 9.3  | 42  |                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                   |
| Total                                                      |      |                                                |                                                                                                       | 921 | 100  | 74* |                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                   |

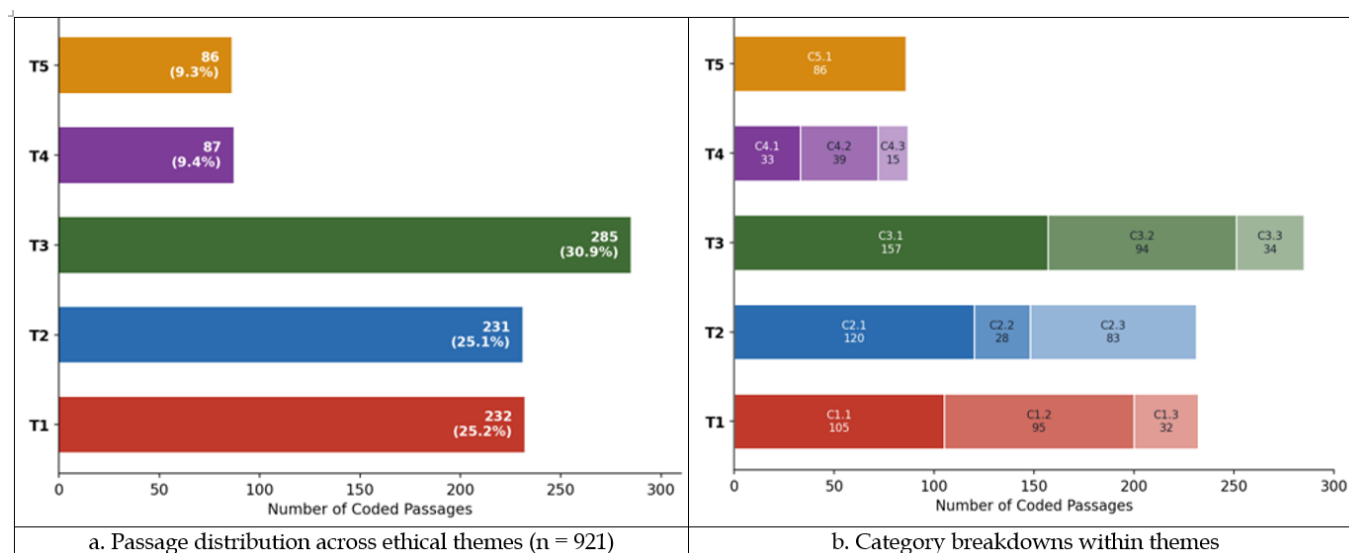
Note. N: Number of studies; \*All 74 included articles contributed coded passages; most appeared in more than one theme, reflecting the cross-cutting nature of ethical issues in AI sustainability contexts; The “example articles” section lists each study once under its dominant (plurality) category, so that all 74 studies appear at least once; entries marked; <sup>†</sup>The studies are representative studies for the three categories (C2.2, C4.1, C4.3) that are not the dominant focus of any single study

social, and governance dimensions of sustainability at the intersection of AI and generative AI (GenAI) ethics. The full taxonomy, including the thirteen categories, passage frequencies, and number of articles, is presented in **Table 3**.

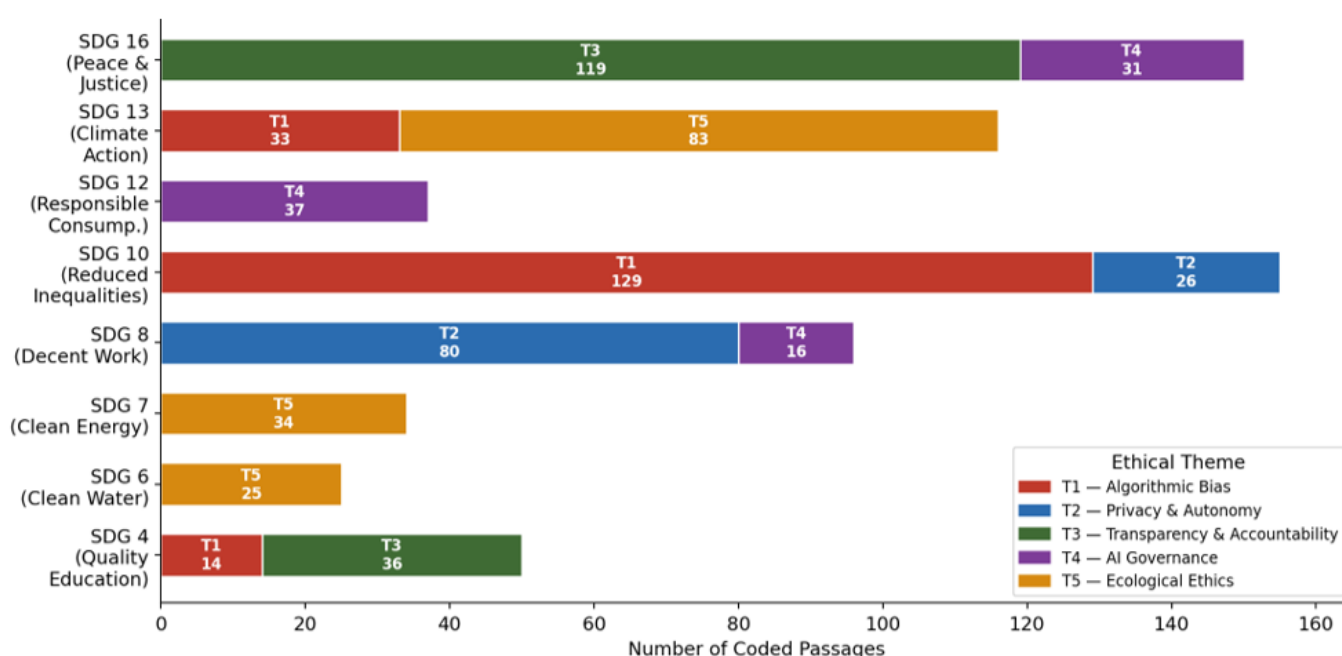
The distribution of passages across the themes and their alignment with the SDGs are shown in **Figure 4** and **Figure 5**, respectively. Educational research is markedly underrepresented in the corpus: 5 of the 74 studies (6.8%) are set in an educational context, and none reports research in science or mathematics education. Across the five themes, a fundamental tension recurs between the transformative potential attributed to AI and the

systemic harms caused by its uncritical application to people, ecosystems, and institutions.

The five themes are the outcome of the coding process and do not map one to one onto the four clusters set out in the conceptual framework. Three clusters were confirmed: environmental costs correspond to T5 (86 passages), algorithmic bias and systemic risks to T1 (232 passages), and the critique of governance and frameworks to T4 (87 passages). The justice and inclusivity cluster did not survive as a theme in its own right, and the passages that carry it were coded under exclusion and marginalization (C1.2), the digital divide and the Global South (C1.3), and the geographic distribution of ecological costs within T5. Two themes



**Figure 4.** Distribution of coded passages across five ethical themes (a) and category breakdown within themes (b) (created by the authors)



**Figure 5.** SDG alignment of ethical themes across the reviewed literature (Values are derived by combining study-level SDG tags with the theme distribution of each study's passages; they indicate relative weight rather than directly coded passage counts) (created by the authors)

were not anticipated by the framework. Transparency, accountability, and epistemic integrity (T3, 285 passages) separated out of the governance cluster and became the largest theme in the sample, while privacy, surveillance, and human autonomy (T2, 231 passages, 25.1 percent) emerged inductively and has no counterpart among the a priori clusters. This divergence is reported as a result rather than smoothed over, since it marks the point at which the conceptual literature and the body of work that addresses the intersection directly part company.

### Ecological Ethics of AI Systems

The ecological footprint of AI systems is the ethical concern with the most direct sustainability implications in the reviewed literature; 86 coded passages (9.3 percent) from 42 articles constitute this theme. Although T5 accounts for the smallest share of passages, one passage fewer than T4 (86 vs. 87), a difference too small to support a ranking, the extent to which ecological concerns permeate discussions within the other four themes demonstrates this theme's conceptual centrality. Training and deploying large language models (LLMs) and GenAI systems requires significant amounts of electricity, water, and rare earth elements; as model scale

and adoption rates increase, so does this demand. Marabelli and Davison (2025) illustrate the scale of this energy demand with the following statement: “The data centers powering AI already account for up to 2% of global energy demand—a figure that is close to what is currently consumed by the airline industry” (p. 1). The carbon impacts of individual model training cycles are equally striking; McNealis (2026) reports that training a single model can result in emissions of “as much as 284 metric tons of CO<sub>2</sub>—roughly equivalent to five times the lifetime emissions of an average automobile in the United States” (p. 408). This picture points to a common consensus that extends beyond a single publication. Melguizo et al. (2026) summarize the situation in their empirical analysis of 23 countries as follows: “AI global boom is currently putting pressure on the environment worldwide, given its intensive use of natural resources, minerals, water and energy” (p. 10).

Water consumption constitutes an equally urgent yet less visible aspect of the ecological burden. A study cited by Marabelli and Davison (2025) notes that GPT-3 “consumes roughly one liter of water to cool down a computer for every 40-100 responses” (p. 4), indicating that global demand could drive data centers to consume trillions of gallons of water in the near future. The deployment of data centers in drought-affected regions deepens this concern, since the corporate expansion of AI appears to conflict with local water security needs. Thus, it can be argued that the ecological ethics of AI systems extend beyond carbon emissions; they encompass a broader resource extraction dynamic with direct implications for SDG 6 (clean water and sanitation), SDG 7 (affordable and clean energy), and SDG 13 (climate action).

The inequality in the geographic distribution of ecological costs constitutes another dimension of this picture. McNealis (2026) describes this asymmetry as follows: “AI benefits are predominantly reaped by global corporations headquartered in the Global North, while emissions and strain on local infrastructures are disproportionately offloaded onto more vulnerable communities” (p. 408). Ricaurte (2022) also points to a similar pattern, noting: “The North-South asymmetric relationship of data flows is an example of this neocolonial data regime” (p. 731). The labor infrastructure of AI development reinforces this asymmetry; the outsourcing of the manual component of model training, that is, the labelling and annotation of data, to low-wage and precarious labor suggests that ecological ethics and social justice cannot be separated from one another.

Lehuedé (2025), while illustrating how the sustainability discourse can be exploited, makes the following observation: “In this vision, being a ‘sustainable’ AI company is not incompatible with resourcing water from Indigenous territories in Chile facing drought” (p. 1767). Philipo et al. (2025), in turn,

highlight the field’s need for “energy efficient algorithms, eco-friendly hardware and ethical governance to mitigate AI’s environmental and social impacts” (p. 1286) as a solution-oriented approach.

Ecological content was not confined to T5. In the open-coding layer that preceded category assignment, 774 of the 910 passages for which open codes are available (85.1%) carried at least one ecological secondary code or sustainability tag; the proportion was 83.6% in T1, 83.0% in T2, 82.3% in T3, and 89.3% in T4. Because the corpus was assembled at the AI-sustainability intersection, a high baseline is expected by construction, and these proportions should not be read as evidence that ecological ethics dominates the other themes. What they do show is that ecological concerns are voiced alongside social and governance concerns within the same passages rather than in a separate strand of the discussion.

### Algorithmic Bias and Unequal AI Outcomes

As shown in part a in [Figure 4](#), with 232 coded passages from 64 articles (25.2 percent), T1 is the second-largest theme in the corpus, closely following T3; at the category level, the largest single category is C3.1 (157 passages, 17.0%). The reviewed literature consistently demonstrates that algorithmic bias is a mechanism through which AI systems reproduce, and in many cases reinforce, existing social and environmental inequalities. This mechanism has particularly significant consequences for environmental justice, health equity, and access to critical resources. McGovern et al. (2022) argue that AI systems trained on underrepresented data “can even perpetuate the bias beyond the regions and circumstances it was trained on” (p. 3). The authors illustrate this point with examples of weather and climate AI tools that systematically exclude communities with low population density, limited sensor infrastructure, or insufficient observational coverage.

Biases in sensor deployment concretely demonstrate how data inequality translates into distributional AI harm at the community level. Drawing on deSouza and Kinney (2021), McGovern et al. (2022) report that popular, low-cost air quality sensors are “deployed in significantly whiter, higher income areas than the national average” (p. 6). This means that communities facing a disproportionate burden of pollution are the least represented in the AI training data designed to monitor and address those very burdens. This finding is supported by numerous other articles in the sample. Nizamani et al. (2026) note that AI “systems often learn from historical data which may include biases that could perpetuate social inequalities” (p. 6) and that “addressing these biases and ensuring fairness in AI outcomes is essential” (p. 6) if AI systems are not to reinforce existing social patterns. Therefore, it can be argued that the relationship between algorithmic bias and sustainability does not remain merely at the

conceptual level; rather, it produces concrete distributional outcomes that undermine the agendas of SDG 10 (reduced inequalities) and SDG 3 (good health and well-being).

The particular vulnerability of Global South communities to these dynamics has been documented in multiple articles in the sample (32 passages, category C1.3). Moyano-Fernández et al. (2024) frame the issue within the context of environmental justice, defining it as follows: “Environmental justice has been mainly conceived as a framework to fairly allocate environmental resources and impacts among unequal people” (p. 3). The fact that communities most vulnerable to climate challenges are often the most disadvantaged in terms of access to AI-supported solutions creates a significant gap between the distribution of AI capabilities and the distribution of climate vulnerability. This gap is considered one of the most significant equity dimensions at the intersection of AI and sustainability and requires special attention in future sustainability research and policy frameworks.

Cina et al. (2025) emphasize: “Models trained on biased datasets can perpetuate or exacerbate inequities in urban systems, such as housing allocation, traffic management and resource distribution” (p. 16). Torres-Rivera et al. (2025) frame the issue by quoting an expert participant: “AI needs an ethical compass, without it, it merely reproduces inequalities” (p. 22).

### **Privacy, Surveillance, and Human Autonomy**

T2 brings together privacy violations, labor displacement, and the erosion of human agency, and comprises 231 coded passages (25.1 percent) from 65 articles. These concerns bear most directly on SDG 8 (decent work and economic growth) and SDG 16 (peace, justice, and strong institutions). Two routes of influence run through the reviewed literature. AI systems affect individuals directly, through data collection and surveillance, and indirectly, through changes in how work and decisions are organized. Nizamani et al. (2026) describe the second route in terms of labor, noting that “potential effects such as job displacement or shifts in worker autonomy need to be carefully managed” (p. 6). The same study argues that guidelines built on user feedback are needed so that AI systems align “with societal values” (p. 8).

The supply chain literature shows how these concerns take shape inside organizations. Bag et al. (2026) describe a “dual challenge”: firms must leverage GenAI in their supply chains while “ensuring ethical, human-centric practices” (p. 5001). Their model was tested with time-lagged survey data from firms in India and South Africa. A digital humanism orientation, which focuses on “human dignity, creativity and value alignment in technological development” (p. 5001), was associated with a more responsible use of GenAI. The

association is conditional rather than fixed. Where professionals work under overlapping crises and job insecurity, “decision making becomes reactive and strategic commitments to circularity may be delayed or deprioritized” (p. 5001). Hence, it can be said that the link between AI ethics and social sustainability is shaped by the organizational and geopolitical setting in which AI is used, which matters above all for firms in developing economies.

Regulation adds a further layer of variation. It is not possible to make a generalization about the privacy dimension of AI ethics, because regulatory regimes differ markedly across countries and regions. Marabelli and Davison (2025) observe that most regulatory interventions to date have addressed data privacy, such as the general data protection regulation in the European Union and the personal information protection law in China. These instruments say little about how AI intersects with environmental and social sustainability. Several authors in the sample treat the EU AI Act as significant because it is the first binding regulatory framework for AI, yet it has been criticized for vague risk definitions and for limited enforcement capacity where environmental harm is concerned. The governance of privacy and human autonomy therefore appears fragmented, and frameworks that combine digital rights with sustainability obligations are still lacking.

Smart cities and small enterprises show the same problem in everyday environments. Riedmann-Streitz et al. (2025) point to invisible sensing infrastructures, noting that “people are not aware of hidden devices and sensors being used for unwanted surveillance without their consent” and that “this is a problem especially in public spaces” (p. 2495). Kittipanya-ngam et al. (2025) report the consequence for trust in a retail setting, where cyber insecurity and the misuse of AI result in “scams and threats that erode trust in online interactions” (p. 9).

### **Transparency, Accountability, and Epistemic Integrity**

As shown in part a in [Figure 4](#), T3 accounts for 285 passages (30.9 percent) from 65 articles, the highest number of passages in the entire sample, reflecting the centrality of concerns regarding transparency and accountability in recent AI ethics literature. The absence of these concerns has been linked to a wide range of sustainability harms, ranging from corporate greenwashing to the erosion of scientific and educational integrity. Marabelli and Davison (2025), noting that the gap is a structural incentive problem, observe that “organizations developing AI models do not have specific incentives to share quantitative data on resources used to build and run such models” (p. 6). In the absence of mandatory reporting requirements, it can be argued that organizations cannot be expected to voluntarily disclose their environmental costs.

The epistemic integrity dimension of this theme is particularly evident in research and educational contexts. In these settings, GenAI's capacity to generate authoritative-sounding texts without properly attributing sources poses a unique threat to knowledge sustainability (category C3.3, 34 passages). Geiger and Di Lazzaro (2025) argue that GenAI outputs "does not always include references to the authors of the sources used for training, which can result in a lack of recognition" and in "the impossibility of users being able to verify whether the output comes from reliable sources" (p. 5). The authors document cases where researchers have discovered articles published under their names but clearly generated by AI; they emphasize that this constitutes a violation of authors' moral rights and undermines the integrity of the academic record. Regarding the educational dimension, the authors note that when students are presented with "gen AI materials trained with inaccurate or incomplete data, their knowledge would be biased and they might lack diverse perspectives or reinforce historical inaccuracies" (p. 6); this situation is directly linked to SDG 4 (quality education) and the sustainability of the information systems through which environmental and climate understanding is generated and transmitted.

Holding AI accountable for its environmental impacts requires not only accountability mechanisms but also enforceable standards with a deterrent effect. McNealis (2026) argues that policy interventions could include regulations mandating "ongoing transparency reporting for AI systems" and requiring organizations to "disclose energy consumption, algorithmic decision-making processes and data provenance" (p. 409); arguing that this would "expose the hidden infrastructures fueling AI and making it more difficult for corporations to externalize environmental costs" (p. 409). In the field of environmental science, McGovern et al. (2022) advocate for the adoption of explainable AI (XAI) approaches as a mechanism to determine, prior to deployment, whether AI models have learned biased or flawed strategies, and emphasize that interpretable AI are "intended to be understandable by human experts" (p. 8), so that a faulty strategy can be identified before deployment.

Alexander et al. (2024) note the following in the agriculture-food context: "Poor performance is excused as within a normal range of algorithmic error, so that food producers cannot hold anyone accountable for the failure" (p. 155). Regarding transparency, Wang et al. (2025) empirically demonstrate that a policy-based intervention "significantly reduces greenwashing in environmental disclosures, confirming its institutional efficacy in terms of enhancing transparency and constraining manipulative behavior" (p. 12).

## AI Governance and Corporate Responsibility

Spanning 44 articles with 87 coded passages (9.4 percent), T4 addresses the governance architecture necessary to transform ethical principles into binding sustainability obligations. It is directly related to SDG 12 (responsible consumption and production) and SDG 16 (peace, justice, and strong institutions). Although T4 ranks fourth in terms of the number of passages, its importance stems from the structural role that governance plays as a mechanism for systematically addressing the harms identified in T1-T3 and T5. In many jurisdictions there is no legislation that considers the environmental impact of AI. Marabelli and Davison (2025) highlight the limitations of voluntary approaches with the following statement: "very few of them will adopt environmentally friendly policies if these policies penalize their bottom line, unless they are legally mandated to do so" (p. 8). This observation underscores the ongoing necessity of binding regulatory tools.

In the context of the supply chain, Bag et al. (2026) present empirical evidence that ethical governance frameworks produce measurable sustainability outcomes. The study finds that "firms that follow ethical GenAI principles like fairness, transparency and accountability have achieved significantly more effective GenAI adoption and performance outcomes" (p. 5002), and that without these foundations, "AI applications can lead to the erosion of sustainability objectives or the exacerbation of structural inequalities" (p. 5003). The authors emphasize that the central governance question is no longer merely how to implement GenAI, but "how to do so responsibly amid systemic pressures that complicate governance and behavioral alignment." The observation that "the ethical violations, opacity and greenwashing in supply chains associated with AI are becoming a more common concern" (p. 5001) indicates that accountability pressures on organizations are intensifying alongside the pace of AI adoption.

A review of the literature at the policy level reveals a distinct convergence across several governance approaches. Geiger and Di Lazzaro (2025) argue that a sustainable copyright framework for GenAI must include both transparency provisions and human-centered accountability mechanisms, stating that "an ethical copyright framework for Gen AI requires balancing various interests, considering sustainability and human rights, while simultaneously incentivizing progress and AI innovation." (p. 11) McNealis (2026), meanwhile, states that to mitigate planetary costs, "the integration of sustainability benchmarks into AI research funding and global cooperation on emissions standards are imperative." Along with calls to integrate AI development into international environmental agreements, these proposals point toward a multilevel governance architecture that combines individual and organizational accountability with sectoral and international regulatory frameworks; this approach is

consistent with the multiscale logic of sustainability governance.

Cordeiro et al. (2026), regarding the EU AI Act, note: “By linking AI governance to human rights, transparency, and accountability, the Act shifts corporate responsibility toward stakeholder-oriented risk management” (p. 6). Yassen et al. (2025) point to the need for “stronger AI governance policies and structured data sharing frameworks, along with more eco-friendly AI models for sustainability in the long run” (p. 20) in the context of environmental decision-making.

### Educational Contexts in the Corpus

Five of the 74 included studies (6.8%) are set in an educational context, and none of them reports research in science or mathematics education. Nguyen et al. (2025) apply value-sensitive design to a chatbot for environmental education and report how privacy and autonomy concerns are negotiated with learners; Torres-Rivera et al. (2025) examine the ethical integration of AI into STEAM pedagogies in higher education and argue that AI without an ethical compass reproduces existing inequalities; Balan (2024) analyses the ethical and sustainability challenges of AI in legal education; Abulibdeh et al. (2024) situate AI in education for sustainable development; and Geiger and Di Lazzaro (2025) address the regulation of GenAI in research and education, linking epistemic integrity to SDG 4. The passages contributed by these five studies fall predominantly under T2 and T3, that is, under privacy and autonomy and under transparency and epistemic integrity, rather than under the ecological theme. Given that the search string contained no education-specific terms, this proportion cannot be read as an estimate of the size of the educational literature on AI ethics; it does indicate, however, that educational research is marginal in the body of work that explicitly addresses the AI-sustainability intersection.

## DISCUSSION

The findings indicate that the relationship between AI ethics and sustainability cannot be reduced to a single axis. It is a five-theme problem area that spans the environmental, social, and governance dimensions of sustainability. One tension recurs across the themes: AI is credited with transformative potential, while its uncritical use generates systemic harms for people, ecosystems, and institutions. This dual reading is consistent with Vinuesa et al. (2020), who show that AI can both support and hinder the SDGs, and with van Wynsberghe (2021), who distinguishes “AI for sustainability” from “the sustainability of AI.” Practice-oriented reviews (Kulkov et al., 2024; Toderas, 2025) and technically focused green AI reviews (Bolón-Canedo et al., 2024) treat the normative dimension as secondary. The present review places ethical issues at the center

instead, and the results suggest that the two readings are more informative when they are held together than when either is taken alone.

The theme of ecological costs accounts for the smallest share of passages. The difference from governance is a single passage (86 vs. 87), which is too small to support a ranking. What makes this theme central is not its frequency but its distribution, since ecological content appears in 82 to 89 percent of the passages coded under the other four themes. This pattern has a parallel to the established literature on AI ethics. In their analysis of 84 ethical guidelines, Jobin et al. (2019) found that sustainability and environmental issues were addressed in only 14 documents, whereas transparency appeared in 86 percent of them. Hagendorff (2020) likewise reported that environmental concerns were relatively neglected in the guidelines he examined. The present findings confirm that neglect at the level of frequency. They also show that, in a sample where the intersection itself is the focus, ecological concerns are voiced alongside social and governance concerns rather than in a separate strand. The findings on AI’s demand for energy, water, and minerals are consistent with Strubell et al. (2019) on the energy costs of deep learning, Kaack et al. (2022) on greenhouse gas impacts, and Ligozat et al. (2022) on hidden environmental impacts. The unequal geographic distribution of the ecological burden turns these costs into a question of justice, which connects the theme to the literature on intergenerational and distributive justice (Barry, 1997; Spijkers, 2018).

Transparency, accountability, and epistemic integrity produced the largest number of passages in the sample. A similar emphasis is reported in the wider AI ethics literature: Jobin et al. (2019) and Corrêa et al. (2023), who analyzed 200 documents, both identify transparency among the most frequently cited principles. The comparison should be read with care, since those studies count documents while the present review counts passages. What this review adds is the setting in which the principle is invoked. Here transparency is discussed in terms of environmental disclosure and greenwashing, a connection that has received limited attention in the general AI ethics literature. The observation that organizations have little incentive to disclose environmental costs is consistent with Heilinger et al. (2024), who warn that the “sustainable AI” narrative is open to abuse. Hence, it can be said that transparency functions as a structural prerequisite for sustainable AI rather than as a procedural add-on.

Algorithmic bias and privacy show how closely the social dimension of sustainability is bound to the ethics of AI. Where biased systems reproduce existing inequalities, the principle of intragenerational justice in sustainable development is put at risk (Langhelle, 1999). This reading is consistent with Mittelstadt (2019), who argues that ethical principles alone do not guarantee fair

outcomes. The concerns raised about privacy and human autonomy point in the same direction, since sustainability rests on institutional and individual foundations as well as environmental ones, which is the position developed by Waelen and van Wynsberghe (2025). Taken together, the two themes suggest that social sustainability belongs to the design of AI systems rather than to a later stage of implementation.

Governance and corporate responsibility occupy a structural position in relation to the harms identified in the other themes. Across the sample, authors converge on the view that voluntary approaches are not sufficient on their own and that binding frameworks are required. This convergence is a convergence of argument rather than evidence of effectiveness, since the corpus consists of ethical analyses rather than evaluations of regulatory instruments. The position is consistent with Mittelstadt (2019) on the gap between principles and practice, and with the third-wave thesis of Bolte and van Wynsberghe (2025), which locates the ethical focus in structural regulation rather than in individual conduct. Regulation alone, however, appears insufficient, and transparency, participation, and institutional accountability are presented in the sample as working together.

The themes are not isolated from one another. Of the 74 included studies, 72 contributed passages to at least two themes, 67 to at least three, and 18 to all five. Responsible AI is most often discussed together with transparency and regulatory governance. The picture can be widened by contributions that go beyond a human-centered framework: Bossert and Hagendorff (2023) argue that sustainable AI must take non-human beings into account, while Nordgren (2023) sets out the dual role of AI in relation to the climate. These relationships are not context-independent. The link between ethics and sustainability is shaped by the organizational and geopolitical environments in which AI is used, which makes the design of governance frameworks a matter of particular importance in developing economies. One context, however, is almost absent from the sample. Only five of the 74 studies are set in education, and none reports research in science or mathematics education. The implications of the five themes for these fields are therefore developed separately below.

### **Implications for Science, Mathematics, and Technology Education**

The five themes were derived from a corpus in which educational research is a small minority, yet each of them bears directly on what science, mathematics, and technology education might teach about AI and on how schools and teacher education programs might use it.

The ecological ethics of AI translates most readily into quantitative classroom work. The figures reported in the corpus are teachable. Training a single large model

has been associated with emissions on the order of 284 metric tons of CO<sub>2</sub>, roughly five times the lifetime emissions of an average automobile in the United States (McNealis, 2026). Inference has been estimated to consume approximately one liter of water for every 40 to 100 responses (Marabelli & Davison, 2025). A unit in which students log their own use of a generative system for a week and estimate the associated water and carbon load turns an abstract externality into a modelling task. Such a task involves unit conversion, proportional reasoning, and order-of-magnitude estimation, and it connects to the socio-scientific issues tradition in science education.

Algorithmic bias becomes concrete in the classroom through data justice. The finding that low-cost air-quality sensors are deployed in affluent, predominantly white areas at rates far above the national average (deSouza & Kinney, 2021, reported in McGovern et al., 2022) is an instance of sampling bias that students can investigate with open environmental data for their own neighborhoods. Such a unit supports a learning objective of the form “questions the representativeness of a data set and explains, with examples, how under-representation affects scientific conclusions”, and it connects naturally to citizen-science approaches, whose collaborative potential is discussed in the corpus (Fraisl et al., 2025).

Privacy, surveillance, and autonomy reach schools as learning analytics. The observation that people are frequently unaware of the devices and sensors collecting data around them (Riedmann-Streitz et al., 2025) applies to attention tracking, proctoring software, and dashboards in ordinary classrooms. A short professional-development module in which teachers inventory the tools that collect data in their own classroom and apply a data-minimization checklist makes the theme actionable. The value-sensitive design approach developed for an environmental-education chatbot (Nguyen et al., 2025) can also be reused as a stakeholder-value analysis exercise for pre-service teachers evaluating an educational AI tool.

Transparency, accountability, and epistemic integrity map onto AI literacy and assessment policy. Where students work with generative material trained on incomplete or incorrect data, their knowledge may be biased and historical inaccuracies may be reinforced (Geiger & Di Lazzaro, 2025), a risk that bears directly on SDG 4. Three responses follow. The first is a curriculum objective concerned with verifying the provenance of AI output and tracing the evidence chain of a scientific claim. The second is a classroom adaptation of XAI, in which students are asked why a model produced a given prediction, mirroring the expert review of potentially flawed strategies described by McGovern et al. (2022). The third is an assessment design that makes the process visible rather than only the product.

Governance and corporate responsibility have a school-level counterpart in procurement and in greenwashing literacy. The argument that firms adopt environmentally costly policies only when legally required to do so (Marabelli & Davison, 2025) applies to institutions choosing educational technology. A teacher-education unit on the ethics of EdTech procurement can examine a product's data policy, energy disclosure, and redress mechanism as a case. Corporate misrepresentation of environmental credentials (Wang et al., 2025) supports a complementary activity in which students evaluate a technology company's sustainability report by matching claims to evidence, with the observation that being a "sustainable" AI company is not incompatible with resourcing water from Indigenous territories facing drought (Lehuedé, 2025, p. 1767) as an opening case.

Two implications for research follow. First, the near absence of science and mathematics education research at this intersection is itself a finding: the ethical debate about AI and sustainability is being conducted largely without educational researchers. Second, the five themes offer a ready structure for that missing work, as a content framework for AI-literacy instruments, as design criteria for teaching materials, and as an agenda for studies of how students reason about the environmental and distributive costs of the tools they use every day.

This study has several limitations, and each is stated together with the direction in which it may have affected the results. The search was restricted to Scopus and WoS and to peer-reviewed publications in English; IEEE Xplore, the ACM digital library, and philosophy indexes were not searched, so engineering and philosophical work at this intersection is probably under-represented, as are non-English and grey literature. The search string contained no terms specific to GenAI or LLMs and no education-specific terms; publications focused on generative systems entered the corpus only when they also used the umbrella term AI, and educational research is under-represented for the same reason. The review was not registered in a protocol registry, which limits external verification of post hoc decisions such as the exclusion of review-type studies at the full-text stage. The 124 records classified as borderline were not advanced to full-text review; their inclusion might have shifted the relative weight of the themes, most plausibly towards the applied and sectoral literature. Passage-level coding was carried out predominantly by a single coder. The full texts of all 74 included studies were read in their entirety, and every extracted passage was verified programmatically against its source. The limitation therefore concerns the absence of a second independent coder rather than the depth of engagement with the sources. Because the independent re-code covered 25 passages (2.7%), no intercoder agreement coefficient can be reported for this stage. The assignments most exposed to this limitation are those at

the boundary between ecological inequity (C1.3) and ecological cost (C5.1). Quantifying passage-level agreement on a larger, blind sample is a priority for future work with this data set, which is available on request. Passage counts index how frequently an issue is voiced rather than how important it is. The different extraction rules applied to empirical and conceptual studies mean that the theme distribution partly reflects the composition of the corpus. The granularity of the taxonomy also affects the ranking, since C5.1 was not subdivided into carbon, water, and extraction categories, while labor displacement is grouped under privacy and autonomy. The SDG values in Figure 5 are derived from study-level tags rather than coded at passage level. Finally, the corpus is a literature about ethics rather than evidence about the effects of governance instruments, so the policy implications drawn here describe convergence among authors rather than demonstrated effectiveness.

## CONCLUSION

This study is an attempt to highlight ethical issues at the intersection of AI ethics and sustainability through direct passages. The findings indicate that this intersection constitutes a holistic problem area encompassing environmental, social, and governance dimensions. When considered individually, the five themes offer a partial picture; when read together, they present a coherent picture.

The key takeaway from the findings is that sustainable AI is not merely a matter of technical efficiency. The ecological costs of AI, distributive justice, and governance gaps require a normative framework that goes beyond technical solutions. Transparency and accountability, as argued above, function as structural prerequisites within this framework rather than as procedural additions to it.

At the policy level, there is a need for binding regulations addressing the environmental impact of AI, mandatory transparency reporting, and frameworks that ensure distributive justice. It is recommended that future research include literature reviews covering non-English-language sources, sector-specific comparisons, and longitudinal studies. Such studies could reveal in greater detail how the relationship between ethics and sustainability varies depending on the context.

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**AI statement:** During revision, the tools were used to check quotations against the source publications, to tabulate the quality appraisal, and for language editing. The authors take full responsibility for the content of the manuscript, including every analytical decision and every claim made.

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**Data sharing statement:** The completed PRISMA 2020 checklist, the study-level quality appraisal, and the characteristics of the included studies are provided as [Supplementary File 1](#), [Supplementary File 2](#), and [Supplementary File 3](#), respectively. The coding framework and the passage-level data set (n = 921) are available from the corresponding author on reasonable request.

## REFERENCES

- Abulibdeh, A., Zaidan, E., & Abulibdeh, R. (2024). Navigating the confluence of artificial intelligence and education for sustainable development in the era of Industry 4.0: Challenges, opportunities, and ethical dimensions. *Journal of Cleaner Production*, 437, Article 140527. <https://doi.org/10.1016/j.jclepro.2023.140527>
- Addison, L. (2026). Ethical governance and artificial intelligence for climate resilience in small island developing states. *Journal of Information, Communication and Ethics in Society*, 24(2), 234-249. <https://doi.org/10.1108/JICES-04-2025-0093>
- Alexander, C. S., Yarborough, M., & Smith, A. (2024). Who is responsible for 'responsible AI'? Navigating challenges to build trust in AI agriculture and food system technology. *Precision Agriculture*, 25(1), 146-185. <https://doi.org/10.1007/s11119-023-10063-3>
- Alghamdi, S. M., Chikwendu, O. C., Chukwuma, O. U., Okech, D. O., Okwu, M. O., Khalid, S., & Vlachostergiou, A. (2025). Navigating ethical challenges in digital transformation: Insights on climate adaptation, microbiology, healthcare, robotics, and AI under the EU AI Act: An experts' panel discussion. *Global Bioethics*, 36(1), Article 2550823. <https://doi.org/10.1080/11287462.2025.2550823>
- Ali, M. G., Jasim, A. K., Abdulrahman, S. A. R., Abu-AlShaeer, M. J., & Mahdi, A. F. (2025). AI ethics, legal regulation, and public trust in environmental health and safety. *Environment and Social Psychology*, 10(9), Article 3945. <https://doi.org/10.59429/esp.v10i9.3945>
- Amore, G., & Gentili, A. (2026). AI and climate: An ethical sustainability framework for balancing risks and responsibilities. *AI & SOCIETY*, 41, 2581-2591. <https://doi.org/10.1007/s00146-025-02615-0>
- Anbarasi, G., & Sankar, D. (2025). Greening the justice system: Assessing the legality, feasibility, and potential of artificial intelligence in advancing environmental sustainability within the Indian judiciary. *Frontiers in Political Science*, 7. <https://doi.org/10.3389/fpos.2025.1553705>
- Apaolaza, V., Paredes, M. R., Hartmann, P., & Eletxigerra, A. (2026). Why artificial intelligence-based emotion monitoring in livestock matters: Effects on meat quality perceptions and consumer purchase intentions. *Food Quality and Preference*, 138, Article 105841. <https://doi.org/10.1016/j.foodqual.2025.105841>
- Bag, S., Rahman, M. S., Routray, S., & Sreedharan, V. R. (2026). Human-centric generative AI in circular supply chains: Theoretical insights from ethics, dynamic capabilities, and resource conservation. *Business Strategy and the Environment*, 35(4), 5000-5029. <https://doi.org/10.1002/bse.70280>
- Balan, A. (2024). Examining the ethical and sustainability challenges of legal education's AI revolution. *International Journal of the Legal Profession*, 31(3), 323-348. <https://doi.org/10.1080/09695958.2024.2421179>
- Barry, B. (1997). Sustainability and intergenerational justice. *Theoria*, 44(89), 43-64. <https://doi.org/10.3167/004058197783593443>
- Bartmann, M. (2022). The ethics of AI-powered climate nudging—How much AI should we use to save the planet? *Sustainability*, 14(9), Article 5153. <https://doi.org/10.3390/su14095153>
- Baum, S. D., & Owe, A. (2023). Artificial intelligence needs environmental ethics. *Ethics, Policy & Environment*, 26(1), 139-143. <https://doi.org/10.1080/21550085.2022.2076538>
- Bolón-Canedo, V., Morán-Fernández, L., Cancela, B., & Alonso-Betanzos, A. (2024). A review of green artificial intelligence: Towards a more sustainable future. *Neurocomputing*, 599, Article 128096. <https://doi.org/10.1016/j.neucom.2024.128096>
- Bolte, L., & van Wynsberghe, A. (2025). Sustainable AI and the third wave of AI ethics: A structural turn. *AI and Ethics*, 5(2), 1733-1742. <https://doi.org/10.1007/s43681-024-00522-6>
- Bolte, L., Vandemeulebroucke, T., & van Wynsberghe, A. (2022). From an ethics of carefulness to an ethics of desirability: Going beyond current ethics approaches to sustainable AI. *Sustainability*, 14(8), Article 4472. <https://doi.org/10.3390/su14084472>
- Bossert, L. N., & Hagendorff, T. (2023). The ethics of sustainable AI: Why animals (should) matter for a sustainable use of AI. *Sustainable Development*, 31(5), 3459-3467. <https://doi.org/10.1002/sd.2596>

- Bostrom, A., Demuth, J. L., Wirz, C. D., Cains, M. G., Schumacher, A., Madlambayan, D., Bansal, A. S., Bearth, A., Chase, R., Crosman, K. M., Ebert-Uphoff, I., Gagne, D. J., Guikema, S., Hoffman, R., Johnson, B. B., Kumler-Bonfanti, C., Lee, J. D., Lowe, A., McGovern, A., ... Williams, J. K. (2024). Trust and trustworthy artificial intelligence: A research agenda for AI in the environmental sciences. *Risk Analysis*, 44(6), 1498-1513. <https://doi.org/10.1111/risa.14245>
- Bourgeois-Gironde, S. (2025). AI as guardians of the commons: Artificial agency and the democratic representation of ecological systems. *Philosophy & Technology*, 38, Article 142. <https://doi.org/10.1007/s13347-025-00966-6>
- Chen, X., Jaffari, A. A., Muzaffar, A., & Rahman, N. (2026). Integrating explainable AI and corporate social responsibility for sustainable practices. *Technological Forecasting & Social Change*, 223, Article 124444. <https://doi.org/10.1016/j.techfore.2025.124444>
- Cina, E., Elbasi, E., Elmazi, G., & AlArnaout, Z. (2025). The role of AI in predictive modeling for sustainable urban development: Challenges and opportunities. *Sustainability*, 17(11), Article 5148. <https://doi.org/10.3390/su17115148>
- Cordeiro, C. M., Adomaitis, L., & Huang, L. (2026). The AI-policy-governance nexus: How regulation and AI shift corporate governance toward stakeholders. *Technology in Society*, 84, Article 103117. <https://doi.org/10.1016/j.techsoc.2025.103117>
- Corrêa, N. K., Galvão, C., Santos, J. W., Del Pino, C., Pinto, E. P., Barbosa, C., Massmann, D., Mambrini, R., Galvão, L., Terem, E., & de Oliveira, N. (2023). Worldwide AI ethics: A review of 200 guidelines and recommendations for AI governance. *Patterns*, 4(10), Article 100857. <https://doi.org/10.1016/j.patter.2023.100857>
- Corsini, F., Annesi, N., & Frey, M. (2025). The role of AI in museums' journey toward sustainable development: Socio-technical imaginaries of a cultural and organizational transformation. *Technovation*, 146, Article 103280. <https://doi.org/10.1016/j.technovation.2025.103280>
- Cugurullo, F., & Xu, Y. (2025). When AIs become oracles: Generative artificial intelligence, anticipatory urban governance, and the future of cities. *Policy and Society*, 44(1), 98-115. <https://doi.org/10.1093/polsoc/puae025>
- Dara, R., Hazrati Fard, S. M., & Kaur, J. (2022). Recommendations for the ethical and responsible use of artificial intelligence in digital agriculture. *Frontiers in Artificial Intelligence*, 5. <https://doi.org/10.3389/frai.2022.884192>
- deSouza, P., & Kinney, P. L. (2021). On the distribution of low-cost PM<sub>2.5</sub> sensors in the US: Demographic and air quality associations. *Journal of Exposure Science & Environmental Epidemiology*, 31(3), 514-524. <https://doi.org/10.1038/s41370-021-00328-2>
- Dhiman, R., Miteff, S., Wang, Y., Ma, S.-C., Amirikas, R., & Fabian, B. (2024). Artificial intelligence and sustainability: A review. *Analytics*, 3(1), 140-164. <https://doi.org/10.3390/analytics3010008>
- Di Chiacchio, L., Al-Khateeb, H., Butt, U., & Yussof, S. (2026). AI legitimacy in energy: A model to improve corporate narratives on sustainability and responsibility. *Technological Forecasting & Social Change*, 222, Article 124378. <https://doi.org/10.1016/j.techfore.2025.124378>
- Fang, M., Nguyen, V. T., Le Minh, T., Louie, J., Pham, L. N., & Hewson, C. (2026). Leadership networks: Shaping AI innovations through responsible practices in Vietnamese tourism and hospitality firms. *Tourism Management*, 113, Article 105317. <https://doi.org/10.1016/j.tourman.2025.105317>
- Fraisl, D., See, L., Fritz, S., Haklay, M., & McCallum, I. (2025). Leveraging the collaborative power of AI and citizen science for sustainable development. *Nature Sustainability*, 8(2), 125-132. <https://doi.org/10.1038/s41893-024-01489-2>
- Fundira, M., Edoun, E. I., & Pradhan, A. (2024). Evaluating end-users' digital competencies and ethical perceptions of AI systems in the context of sustainable digital banking. *Sustainable Development*, 32(5), 4866-4878. <https://doi.org/10.1002/sd.2945>
- Galaz, V., Centeno, M. A., Callahan, P. W., Causevic, A., Patterson, T., Brass, I., Baum, S., Farber, D., Fischer, J., Garcia, D., McPhearson, T., Jimenez, D., Helbing, D., Nesterova, K., & Levy, K. (2021). Artificial intelligence, systemic risks, and sustainability. *Technology in Society*, 67, Article 101741. <https://doi.org/10.1016/j.techsoc.2021.101741>
- Geiger, C., & Di Lazzaro, F. (2025). Sustainability as a guiding principle for copyright reform: Regulating the use of generative AI in the field of research and education. *Discover Sustainability*, 6, Article 1032. <https://doi.org/10.1007/s43621-025-01918-y>
- Ghamisi, P., Yu, W., Marinoni, A., Gevaert, C. M., Persello, C., Selvakumaran, S., Giroto, M., Horton, B. P., Rufin, P., Hostert, P., Pacifici, F., & Atkinson, P. M. (2025). Responsible artificial intelligence for Earth observation: Achievable and realistic paths to serve the collective good. *IEEE Geoscience and Remote Sensing Magazine*, 13(3), 72-95. <https://doi.org/10.1109/MGRS.2025.3529726>

- Goralski, M. A., & Tan, T. K. (2020). Artificial intelligence and sustainable development. *The International Journal of Management Education*, 18(1), Article 100330. <https://doi.org/10.1016/j.ijme.2019.100330>
- Guzmán Rincón, A., Amado Mateus, M., & Martín-Caro Álamo, E. (2026). Determinant variables in the responsible consumption of artificial intelligence (AI) from the perspective of non-specialized users in Colombia. *Asia-Pacific Journal of Business Administration*, 18(4), 1091-1108. <https://doi.org/10.1108/apjba-02-2025-0119>
- Hagendorff, T. (2020). The ethics of AI ethics: An evaluation of guidelines. *Minds and Machines*, 30(1), 99-120. <https://doi.org/10.1007/s11023-020-09517-8>
- Heilinger, J.-C., Kempt, H., & Nagel, S. (2024). Beware of sustainable AI! Uses and abuses of a worthy goal. *AI and Ethics*, 4(2), 201-212. <https://doi.org/10.1007/s43681-023-00259-8>
- Hendawy, M., & Ghaz, L. (2024). A starting framework for urban AI applications. *Ain Shams Engineering Journal*, 15(11), Article 102987. <https://doi.org/10.1016/j.asej.2024.102987>
- Herrera-Vega, E. (2022). Harnessing ethical AI surveillance for climate change governmentality. *Transdisciplinary Journal of Engineering & Science*, SP-3, 129-146. <https://doi.org/10.22545/2022/00205>
- Javed, K., & Li, J. (2025). Bias in adjudication: Investigating the impact of artificial intelligence, media, financial, and legal institutions in pursuit of social justice. *PLoS ONE*, 20(1), Article e0315270. <https://doi.org/10.1371/journal.pone.0315270>
- Jobin, A., Ienca, M., & Vayena, E. (2019). The global landscape of AI ethics guidelines. *Nature Machine Intelligence*, 1(9), 389-399. <https://doi.org/10.1038/s42256-019-0088-2>
- Kaack, L. H., Donti, P. L., Strubell, E., Kamiya, G., Creutzig, F., & Rolnick, D. (2022). Aligning artificial intelligence with climate change mitigation. *Nature Climate Change*, 12(6), 518-527. <https://doi.org/10.1038/s41558-022-01377-7>
- Katirai, A. (2024). The environmental costs of artificial intelligence for healthcare. *Asian Bioethics Review*, 16(4), 527-538. <https://doi.org/10.1007/s41649-024-00295-4>
- Khakurel, J., Penzenstadler, B., Porras, J., Knutas, A., & Zhang, W. (2018). The rise of artificial intelligence under the lens of sustainability. *Technologies*, 6(4), Article 100. <https://doi.org/10.3390/technologies6040100>
- Kiettikunwong, N., Narot, P., & Deod, P. (2025). Advancing disability inclusion in Thailand through AI for sustainable development. *International Journal of Developmental Disabilities*, 71(6), 919-928. <https://doi.org/10.1080/20473869.2025.2521666>
- Kittipanya-ngam, P., Tan, K. H., & Cavite, H. J. (2025). Future-ready AI: A framework for ethical and sustainable adoption. *Technology in Society*, 83, Article 102993. <https://doi.org/10.1016/j.techsoc.2025.102993>
- Kulkarni, A. V., Joseph, S., & Patil, K. P. (2024). Artificial intelligence technology readiness for social sustainability and business ethics: Evidence from MSMEs in developing nations. *International Journal of Information Management Data Insights*, 4(2), Article 100250. <https://doi.org/10.1016/j.jjime.2024.100250>
- Kulkov, I., Kulkova, J., Rohrbeck, R., Menvielle, L., Kaartemo, V., & Makkonen, H. (2024). Artificial intelligence-driven sustainable development: Examining organizational, technical, and processing approaches to achieving global goals. *Sustainable Development*, 32(3), 2253-2267. <https://doi.org/10.1002/sd.2773>
- Langhelle, O. (1999). Sustainable development: Exploring the ethics of our common future. *International Political Science Review*, 20(2), 129-149. <https://doi.org/10.1177/0192512199202002>
- Le Goff, T. (2026). Environmental law's principles applied to artificial intelligence: A path toward regulation. *International Review of Law, Computers & Technology*, 40(1), 74-97. <https://doi.org/10.1080/13600869.2025.2506166>
- Lehuedé, S. (2025). An elemental ethics for artificial intelligence: Water as resistance within AI's value chain. *AI & SOCIETY*, 40, 1761-1774. <https://doi.org/10.1007/s00146-024-01922-2>
- Leikas, J., Johri, A., Latvanen, M., Wessberg, N., & Hahto, A. (2022). Governing ethical AI transformation: A case study of AuroraAI. *Frontiers in Artificial Intelligence*, 5. <https://doi.org/10.3389/frai.2022.836557>
- Ligozat, A.-L., Lefevre, J., Bugeau, A., & Combaz, J. (2022). Unraveling the hidden environmental impacts of AI solutions through a life cycle assessment of AI solutions. *Sustainability*, 14(9), Article 5172. <https://doi.org/10.3390/su14095172>
- Manning, L., Brewer, S., Craigon, P. J., Frey, J., Gutierrez, A., Jacobs, N., Kanza, S., Munday, S., Sacks, J., & Pearson, S. (2022). Artificial intelligence and ethics within the food sector: Developing a common language for technology adoption across the supply chain. *Trends in Food Science & Technology*, 125, 33-42. <https://doi.org/10.1016/j.tifs.2022.04.025>

- Marabelli, M., & Davison, R. M. (2025). Artificial intelligence and the environment: Ethical challenges and strategic opportunities for organizations. *Journal of Strategic Information Systems*, 34, Article 101921. <https://doi.org/10.1016/j.jsis.2025.101921>
- Mazzi, F. (2025). Evaluating the normative implications of national and international artificial intelligence policies for sustainable development goal 3: Good health and well-being. *Health Affairs Scholar*, 3(6), Article qxaf108. <https://doi.org/10.1093/haschl/qxaf108>
- McCormack, L., Bendeckache, M., Lewis, D., & Huyskes, D. (2026). Trust and transparency in AI: Industry voices on data, ethics, and compliance. *AI & SOCIETY*, 41(3), 2311-2339. <https://doi.org/10.1007/s00146-025-02654-7>
- McGovern, A., Ebert-Uphoff, I., Gagne, D. J., II, & Bostrom, A. (2022). Why we need to focus on developing ethical, responsible, and trustworthy artificial intelligence approaches for environmental science. *Environmental Data Science*, 1, Article e6. <https://doi.org/10.1017/eds.2022.5>
- McNealis, R. (2026). Shame in the machine: Affective accountability and the ethics of AI. *AI & SOCIETY*, 41, 403-413. <https://doi.org/10.1007/s00146-025-02472-x>
- Melguizo, A., Katz, R., & Jung, J. (2026). Can AI grow green? Evidence of a Kuznets curve among AI, renewable energies, and emissions. *Energy Policy*, 208, Article 114883. <https://doi.org/10.1016/j.enpol.2025.114883>
- Mittelstadt, B. (2019). Principles alone cannot guarantee ethical AI. *Nature Machine Intelligence*, 1(11), 501-507. <https://doi.org/10.1038/s42256-019-0114-4>
- Mondal, S., Uyen, N. C. T., Das, S., & Vrana, V. G. (2025). Innovation dynamics and ethical considerations of agentic artificial intelligence in the transition to a net-zero carbon economy. *Sustainability*, 17(19), Article 8806. <https://doi.org/10.3390/su17198806>
- Moyano-Fernández, C., Rueda, J., Delgado, J., & Ausín, T. (2024). May artificial intelligence take health and sustainability on a honeymoon? Toward green technologies for multidimensional health and environmental justice. *Global Bioethics*, 35(1), Article 2322208. <https://doi.org/10.1080/11287462.2024.2322208>
- Nadeem, W., Ashraf, A. R., Khan, H., & Kumar, V. (2026). Impact of AI strategies on climate-change performance: Responsible AI and crisis management perspectives. *Technovation*, 150, Article 103390. <https://doi.org/10.1016/j.technovation.2025.103390>
- Neethirajan, S. (2023). The significance and ethics of digital livestock farming. *AgriEngineering*, 5(1), 488-505. <https://doi.org/10.3390/agriengineering5010032>
- Nguyen, H., Nguyen, V., Ludovise, S., & Santagata, R. (2025). Value-sensitive design of chatbots in environmental education: Supporting identity, connectedness, well-being, and sustainability. *British Journal of Educational Technology*, 56(4), 1370-1390. <https://doi.org/10.1111/bjet.13568>
- Nishant, R., Kennedy, M., & Corbett, J. (2020). Artificial intelligence for sustainability: Challenges, opportunities, and a research agenda. *International Journal of Information Management*, 53, Article 102104. <https://doi.org/10.1016/j.ijinfomgt.2020.102104>
- Nizamani, M. M., Qureshi, S., Tarashkar, M., Zhang, H.-L., Zhou, Q., & Lai, Z. (2025). Ethical AI: Human-centered approaches for adaptive and sustainable urban planning and policy. *Land Use Policy*, 157, Article 107650. <https://doi.org/10.1016/j.landusepol.2025.107650>
- Nizamani, M. M., Zhang, H.-L., & Lai, Z. (2026). Human-centered AI: Advancing ethical, transparent, and context-aware systems for sustainable development. *Technology in Society*, 84, Article 103121. <https://doi.org/10.1016/j.techsoc.2025.103121>
- Nordgren, A. (2023). Artificial intelligence and climate change: Ethical issues. *Journal of Information, Communication and Ethics in Society*, 21(1), 1-15. <https://doi.org/10.1108/JICES-11-2021-0106>
- Onder, O. (2026). Planetary health in the age of artificial intelligence: A structural-ethical inquiry into sustainable AI in healthcare. *AI & SOCIETY*, 41(3), 1967-1978. <https://doi.org/10.1007/s00146-025-02603-4>
- Ong, J. C. L., Seng, B. J. J., Law, J. Z. F., Low, L. L., Kwa, A. L. H., Giacomini, K. M., & Ting, D. S. W. (2024). Artificial intelligence, ChatGPT, and other large language models for social determinants of health: Current state and future directions. *Cell Reports Medicine*, 5(1), 101356. <https://doi.org/10.1016/j.xcrm.2023.101356>
- Orrù, E. (2026). Small data AI as a more sustainable next-wave AI? Exploring a potential sociotechnical shift away from the voracity of big data. *AI & SOCIETY*, 41(2), 1035-1051. <https://doi.org/10.1007/s00146-025-02608-z>
- Philipo, A. G., Ning, H., Sarwatt, D. S., Mohamed, J. A., Yusufu, A. S., Shi, F., Urenje, S., & Ding, J. (2025). Sustainable AI: Emerging trends, impacts, and future challenges. *IEEE Transactions on Sustainable Computing*, 10(6), 1278-1287. <https://doi.org/10.1109/TSUSC.2025.3611272>

- Ricaurte, P. (2022). Ethics for the majority world: AI and the question of violence at scale. *Media, Culture & Society*, 44(4), 726-745. <https://doi.org/10.1177/01634437221099612>
- Richie, C. (2022). Environmentally sustainable development and the use of artificial intelligence in health care. *Bioethics*, 36(5), 547-555. <https://doi.org/10.1111/bioe.13018>
- Riedmann-Streitz, C., Streitz, N., Antona, M., Marcus, A., Margetis, G., Ntoa, S., Rau, P.-L. P., & Rosenzweig, E. (2025). How to create and foster sustainable smart cities? Insights on ethics, trust, privacy, transparency, incentives, and success. *International Journal of Human-Computer Interaction*, 41(4), 2491-2522. <https://doi.org/10.1080/10447318.2024.2325175>
- Rohde, F., Wagner, J., Meyer, A., Reinhard, P., Voss, M., Petschow, U., & Mollen, A. (2024). Broadening the perspective for sustainable artificial intelligence: Sustainability criteria and indicators for artificial intelligence systems. *Current Opinion in Environmental Sustainability*, 66, Article 101411. <https://doi.org/10.1016/j.cosust.2023.101411>
- Shaikhon, A. M. H. (2025). Contextual ethical framework for artificial intelligence in the management of cultural heritage. *STAR: Science & Technology of Archaeological Research*, 11(1), Article e2564519. <https://doi.org/10.1080/20548923.2025.2564519>
- Shussett, D., & Dubljević, V. (2025). Applying the agent-deed-consequence (ADC) model to smart city ethics. *Algorithms*, 18(10), Article 625. <https://doi.org/10.3390/a18100625>
- Simion, R. (2025). Ethical dimensions of AI within cyber-integrated ecosystems. *Studia Universitatis Philosophia*, 70(1), 105-120. <https://doi.org/10.24193/subbphil.2025.1.05>
- Spijkers, O. (2018). Intergenerational equity and the sustainable development goals. *Sustainability*, 10(11), Article 3836. <https://doi.org/10.3390/su10113836>
- Strubell, E., Ganesh, A., & McCallum, A. (2019). Energy and policy considerations for deep learning in NLP. In *Proceedings of the 57<sup>th</sup> Annual Meeting of the Association for Computational Linguistics* (pp. 3645-3650). Association for Computational Linguistics. <https://doi.org/10.18653/v1/P19-1355>
- Tian, B., Deng, Z., Gulzar, M. A., & Yu, J. (2026). Artificial intelligence and the rise of corporate digital responsibility: Unlocking ethical governance. *Corporate Social Responsibility and Environmental Management*, 33(2), 1954-1969. <https://doi.org/10.1002/csr.70254>
- Toderas, M. (2025). Artificial intelligence for sustainability: A systematic review and critical analysis of AI applications, challenges, and future directions. *Sustainability*, 17(17), Article 8049. <https://doi.org/10.3390/su17178049>
- Tong, S., & Li, S. (2024). Explainable artificial intelligence for urban planning: Challenges, solutions, and future trends from a new perspective. *International Journal of Advanced Computer Science and Applications*, 15(7), 779-787. <https://doi.org/10.14569/IJACSA.2024.0150777>
- Torres-Rivera, A. D., Rendón Peña, A. A., Díaz-Torres, S. T., & Díaz-Torres, L. A. (2025). Ethical integration of AI and STEAM pedagogies in higher education: A sustainable learning model for Society 5.0. *Sustainability*, 17(19), Article 8525. <https://doi.org/10.3390/su17198525>
- van der Ven, H., Corry, D., Elnur, R., Provost, V. J., Syukron, M., & Tappauf, N. (2025). Does artificial intelligence bias perceptions of environmental challenges? *Environmental Research Letters*, 20(1), Article 014009. <https://doi.org/10.1088/1748-9326/ad95a2>
- van Wynsberghe, A. (2021). Sustainable AI: AI for sustainability and the sustainability of AI. *AI and Ethics*, 1(3), 213-218. <https://doi.org/10.1007/s43681-021-00043-6>
- Vann Yaroson, E., Abadie, A., & Roux, M. (2025). Human-artificial intelligence collaboration in supply chain outcomes: The mediating role of responsible artificial intelligence. *Annals of Operations Research*, 354, 35-69. <https://doi.org/10.1007/s10479-025-06534-7>
- Vargas-Machado, C., & Bedoya, A. R. (2025). The principle of shared utilization of benefits applied to the development of artificial intelligence. *Philosophies*, 10(4), Article 87. <https://doi.org/10.3390/philosophies10040087>
- Vinuesa, R., Azizpour, H., Leite, I., Balaam, M., Dignum, V., Domisch, S., Felländer, A., Langhans, S. D., Tegmark, M., & Fuso Nerini, F. (2020). The role of artificial intelligence in achieving the sustainable development goals. *Nature Communications*, 11, Article 233. <https://doi.org/10.1038/s41467-019-14108-y>
- Waelen, R., & van Wynsberghe, A. (2025). Considering the social and economic sustainability of AI. *Science and Engineering Ethics*, 31(4), Article 19. <https://doi.org/10.1007/s11948-025-00544-1>

- Wang, X., Gao, X., Sun, M., & Zheng, C. (2025). The impact of artificial intelligence on corporate greenwashing: Evidence from the new generation of artificial intelligence innovation and development pilot zones policy. *Environmental Sciences Europe*, 37, Article 216. <https://doi.org/10.1186/s12302-025-01263-x>
- WCED. (1987). *Our common future*. Oxford University Press.
- Yassen, M., Noaman, M. S., Hassan, T. A. M. A., Qasim, N. H., Abbas, I., & Khlaponin, Y. (2025). Big data and AI in environmental decision-making: Legal and ethical challenges. *Environment and Social Psychology*, 10(9), Article 3983. <https://doi.org/10.59429/esp.v10i9.3983>
- Yu, X., Hou, M., & Li, Y. (2026). AI, environment, and lifeworld: How does artificial intelligence influence lived experience in environmental ethics? *AI & SOCIETY*, 41, 4691-4703. <https://doi.org/10.1007/s00146-025-02770-4>
- Zada, M., Khan, S., Mehmood, S., & Contreras-Barraza, N. (2024). Generative artificial intelligence in FinTech: Applications, environmental, social, and governance considerations, and organizational performance: The moderating role of ethical dilemmas. *Oeconomia Copernicana*, 15(4), 1303-1347. <https://doi.org/10.24136/oc.3323>
- Zaidan, E., Truby, J., Ibrahim, I. A., & Hoppe, T. (2026). Hybrid global governance for responsible and inclusive artificial intelligence: Proposing a new sustainable development goal 18. *Technology in Society*, 85, Article 103159. <https://doi.org/10.1016/j.techsoc.2025.103159>
- Zhang, F., Li, J., & Lu, J. (2024). Potential impacts of population aging and artificial intelligence on households, living arrangements, and sustainable development. *China Population and Development Studies*, 8(4), 490-516. <https://doi.org/10.1007/s42379-024-00168-1>
- Zhao, J., & Gómez Fariñas, B. (2023). Artificial intelligence and sustainable decisions. *European Business Organization Law Review*, 24(1), 1-39. <https://doi.org/10.1007/s40804-022-00262-2>

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