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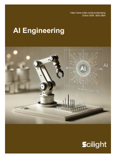

Review

Artificial Intelligence and the Future of Engineering: A Review of Ethical Governance, Societal Transformation, and Environmental Sustainability

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How To Cite: Adelakun, N.O. Artificial Intelligence and the Future of Engineering: A Review of Ethical Governance, Societal Transformation, and Environmental Sustainability. *AI Engineering* **2026**, *2*(2), 15. https://doi.org/10.53941/aieng.2026.100015

Received: 20 June 2026
Revised: 10 July 2026
Accepted: 11 August 2026
Published: 17 August 2026

Abstract: Artificial intelligence (AI) is increasingly being incorporated into engineering practices, transforming the design, construction, operation, and maintenance of systems. The present study explores recent peer-reviewed literature on three interwoven aspects of this transformation: ethical governance, societal change, and environmental sustainability. The review covers new governance instruments such as the European Union Artificial Intelligence Act, ISO/IEC 42001, and the NIST AI Risk Management Framework, as well as explainable-AI (XAI) methods that engineers are increasingly using to explain to regulators, clients, and the public why their safety-critical decisions are made. Also, it addresses the implications of AI on engineering labor markets, professional education and decision-making power, including the differential exposure of high-skill cognitive tasks to automation, and the need for new skills. Furthermore, it considers the dual nature of AI in terms of its contribution to resource optimization, predictive maintenance and integration of renewable energy, and its contribution to an increasing computational carbon and water footprint that can offset these benefits, a tension that is sometimes referred to as the Jevons paradox. The review suggests an integrated framework of responsible AI engineering that connects the three elements of responsible AI: technical explainability, institutional accountability, and life-cycle environmental auditing. The review concludes that long-term acceptability and acceptance of AI in engineering practice will not only be determined by the performance of the models themselves, but also by the ability of the engineering discipline to govern AI transparently, fairly and within planetary limits.

Keywords: artificial intelligence; engineering ethics; AI governance; explainable AI; environmental sustainability; responsible innovation

1. Introduction

The application of new computational tools, whether slide rules, finite-element analysis, or building information modeling, has always been the driver of engineering progress. Artificial Intelligence is a qualitatively new stage in this process as it can not only speed up calculations that engineers already know how to perform, but more and more, it can perform pattern recognition, prediction, and even design synthesis in a way that is hard for human practitioners to fully understand [1,2]. Machine learning models can now help in structural health monitoring, fault diagnosis in manufacturing, traffic and energy-grid optimization, and generative design of components and infrastructure. New technologies are moving from experimental prototypes to safety-critical and large-scale infrastructure applications, and engineers are being faced with more questions than just those about performance.

This review examines three of these questions, which are interrelated and form a single transformation. The first pillar is ethical governance: how can engineers, organizations and regulators ensure that AI-powered systems are safe, explainable and accountable, when increasingly they are deployed in making or supporting consequential decisions in opaque "black-box" models [2,3]? The second pillar is societal transformation: that is, how is AI changing the engineering job market, the distribution of expertise and the relationship between human judgment and automated decision-making [4,5]? The third pillar is environmental sustainability: can AI be used to make engineered systems more resource efficient, while also keeping the resource usage of the AI system itself within ecological bounds [6–8]?

These pillars are not stand-alone. A governance failure, such as the introduction of an unexplainable model in a safety-critical bridge-monitoring system, can have a societal impact by reducing public trust, while also having an environmental and economic impact by causing a retrofit. On the other hand, optimization for sustainability can generate new classes of engineering tasks that were non-existent 10 years ago. The review therefore takes an integrative approach, considering ethics, society, and environment as complementary aspects of one transition instead of separate areas, as suggested in the literature for a more comprehensive view of responsible AI [9,10].

The rest of this review proceeds in the following way. Section 2 provides the scope and drivers for AI use in engineering areas. Section 3 looks at ethical governance structures and explainability needs. The societal and workforce implications of AI in engineering are discussed in Section 4. Section 5 examines the environmental sustainability aspect, exploring how AI can be both a sustainability enabler and a sustainability resource consumer. The integrated framework for Responsible AI Engineering is proposed in Section 6. Limitations and future research directions are discussed in Section 7, with a conclusion in Section 8.

2. Scope and Drivers of AI Adoption in Engineering

Three factors are driving the adoption of AI in engineering: the increasing number of large-scale, sensor-generated datasets from instrumented infrastructure and production lines, the growing sophistication of deep learning architectures that can handle large-scale data, and competitive and regulatory pressures to enhance efficiency, safety, and sustainability performance. AI methods are currently applied to damage detection, predictive maintenance, and design optimization in civil and structural engineering, and the ability to explain is now considered a prerequisite for the professional and regulatory acceptance of an AI system, rather than a nice-to-have. AI is also used in manufacturing and industrial cyber-physical systems for defect detection, process monitoring and quality control, where opacity of the "black-box" models has been recognized as a challenge for operators to trust and safely use in high-stakes production environments [3,11].

In energy and infrastructure engineering, AI is used to predict renewable energy generation, to manage the distribution of energy generation and consumption, and to coordinate energy storage assets, and at the same time consumes significant energy for training models and making predictions, which will be discussed in more detail in Section 5 [12]. In each of these areas, a common theme is that the technical capacity is greater than the institutional capacity needed to manage it responsibly, a theme that is the focus of the next section. Figure 1 shows that core AI technologies are supported by digital infrastructures and data-driven systems, which can be applied to various engineering disciplines to achieve innovation, efficiency, safety, sustainability, and intelligent decision-making.

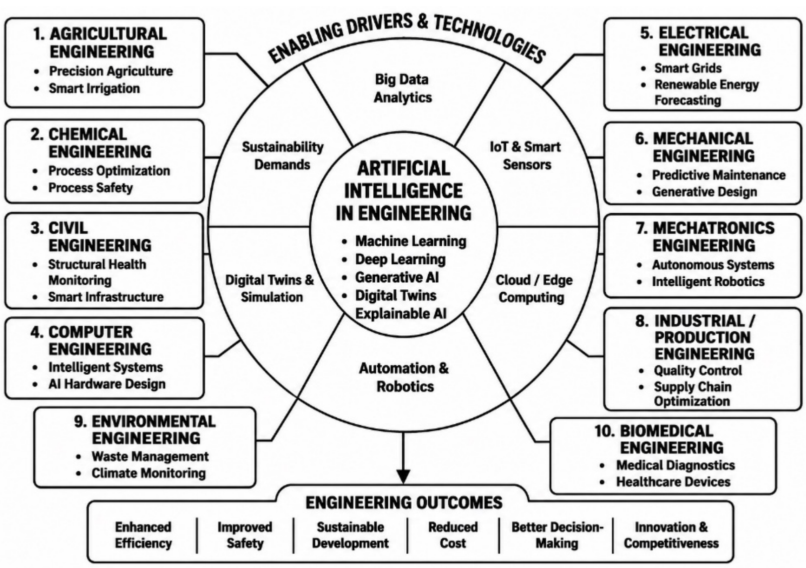

Figure 1. Integrated landscape of artificial intelligence adoption across major engineering disciplines.

3. Ethical Governance of AI in Engineering

3.1. Principles and Emerging Regulatory Frameworks

There is a huge and growing body of literature documenting the growth of AI ethics guidelines from governments, professional bodies, and corporations. In their groundbreaking study on AI ethics guidelines worldwide, Jobin, Ienca and Vayena identified five core principles that were broadly shared, namely, transparency, justice and fairness, non-maleficence, responsibility and privacy, as well as significant differences in the interpretation and implementation of these principles across jurisdictions [13]. This gap has led to criticism that many guidelines are still aspirational and not practically implementable [14,15] and that there are no mechanisms for enforcing, sanctioning, or incentivizing ethical practices in AI [16].

Governance has, in turn, moved from voluntary to binding and quasi-binding instruments. The EU's Artificial Intelligence Act (2024) introduces a risk-based classification system, with AI systems deployed in critical infrastructure, such as many engineering applications, being deemed high-risk and subject to conformity assessment, documentation, and oversight by humans. This is in addition to voluntary management-system frameworks like ISO/IEC 42001 and risk frameworks like the U.S. NIST AI Risk Management Framework, which offer engineering organizations structured processes for identifying, documenting, and mitigating AI-related risk [17,18]. In addition, Camilleri's analysis of AI governance highlights the social responsibility implications of such regulations, noting that the guidance for developers of machine-learning and deep-learning systems is not as well-developed as it needs to be to keep pace with the system's deployment [9]. Complementary scoping exercises of AI governance best practices reveal common challenges, such as ambiguous accountability frameworks, inadequate cross-functional collaboration, and a disconnect between principles and practice in organizations implementing AI [16,19]. Beyond international regulations, context-specific governance models have been suggested for emerging economies, highlighting the importance of institutional alignment between the deployment of AI, academic integrity, and fair access to digital systems in tertiary education settings [20].

3.2. Explainability, Trust, and Engineering Accountability

Engineering ethics has always been based on the idea that the engineer should be able to justify and explain his/her actions to his/her client, regulators, and the public. The difficulty of the principle is compounded by AI as many successful models, especially deep neural networks, are opaque. Explainable AI (XAI) has become a technical solution, which includes techniques that provide interpretability of the model results without compromising too much accuracy [2,3]. Ali and colleagues' extensive survey of XAI highlights the lack of a consensus on the metrics for assessing the quality of an explanation, and the need to think of explainability along with robustness, fairness, and privacy when it comes to trustworthy AI systems [3]. Hassija et al. also consider explainability as a key factor in establishing trust in a black-box model in a consequential domain like manufacturing and infrastructure monitoring [4].

In industrial applications, XAI methods have been used in manufacturing to explain the connection between process variables and the resulting product properties, such as correlating the input variables to an additive-manufacturing process with the resulting tensile strength; by this means, engineers could check the reasoning of their XAI model against materials science principles [21]. These applications represent a larger point: in engineering, explainability is not just a technical capability, but a professional accountability mechanism: engineers must have a duty of care as mandated by licensure and codes of conduct, even when the duty of care is supported by AI [1,2].

3.3. Organizational and Professional Responsibility

In addition to being technically explainable, researchers have increasingly begun to call for the integration of responsible AI into organizational governance processes, rather than just an engineering design challenge. Koniakou documents an evolution in the field from a first phase of "rush to ethics" (which involved voluntary principle-setting) to a "race for governance" (in which institutions race to create binding oversight structures), with direct implications for the way engineering companies manage AI risks and who is held accountable for AI-assisted decisions [22]. Mäntymäki et al.'s hourglass model of organizational AI governance also suggests that there is a need for intermediate organizational mechanisms between high-level ethical principles and concrete decisions on design and deployment, including internal review boards, audit trails, and role-specific accountability [23]. For engineering organisations, it implies that ethical AI governance is not a compliance checklist; it is a continuous institutional responsibility and follows long-standing norms from engineering ethics, which state that the systems one designs are ones that one is responsible for continuously [24]. Data governance research in higher education further indicates that data protection compliance mechanisms are essential to the proper functioning of AI oversight to ensure that learner and institutional data is handled in a lawful, ethical and secure manner [25].

Figure 2 illustrates the hierarchical structure of ethical principles, regulatory frameworks, technical safeguards, and organizational governance mechanisms, all of which contribute to fostering transparency, accountability, trustworthiness, and responsible AI implementation.

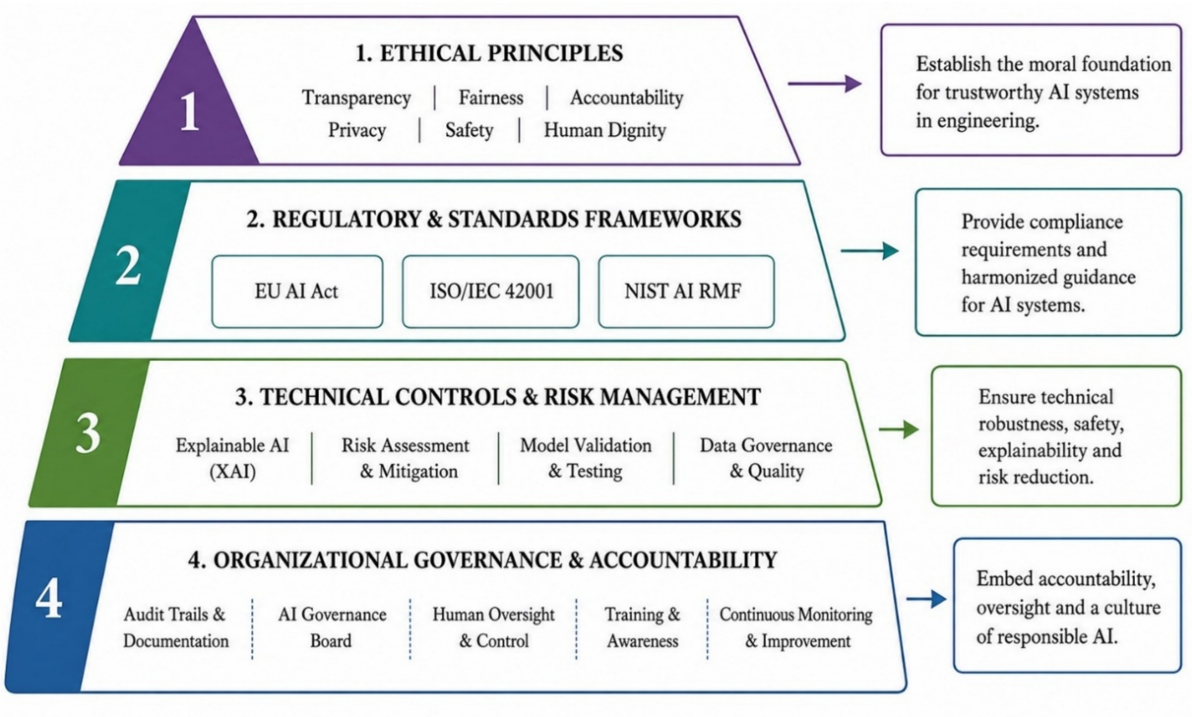

Figure 2. Ethical Governance Framework for Responsible AI Engineering.

The main governance instruments and technical practices discussed above and their relevance to engineering practice are summarised in Table 1.

Table 1. Governance instruments and technical practices relevant to ethical AI in engineering.

Instrument	Type	Primary Mechanism	Relevance to Engineering
EU AI Act (Reg. 2024/1689) [15]	Binding regulation	Risk-tiered conformity assessment	High-risk classification for critical-infrastructure AI
ISO/IEC 42001 [17]	Voluntary standard	AI management system certification	Auditable governance processes for engineering firms
NIST AI Risk Management Framework [18]	Voluntary framework	Risk identification and mitigation lifecycle	Structured risk assessment for AI-enabled systems
Explainable AI (XAI) methods [2,3]	Technical practice	Model-agnostic and intrinsic interpretability tools	Justifying AI-assisted decisions to regulators and clients
Organizational AI governance models [22,23]	Institutional practice	Internal review, audit trails, accountability roles	Embedding ethics into engineering project workflows

4. Societal Transformation: Work, Skills, and Decision-Making

4.1. The Changing Engineering Workforce

AI is not just replacing the repetitive tasks of manual labor, as seen in previous rounds of automation, but also cognitive tasks that were traditionally the domain of highly trained experts, such as engineers [4,5]. The International Monetary Fund (IMF) analysis of generative AI and the future of work projects that a significant portion of work in advanced economies is vulnerable to AI-driven task transformation, that this impact is more likely to be felt by highly educated and cognitively demanding jobs, and that the impact of AI on a given worker depends on whether AI complements or replaces their task [5]. In engineering, this translates to a growing ability to leverage AI assistance for routine analyses, like initial design iterations, code compliance, or typical simulations, while still maintaining the need for licensed engineers to handle tasks that demand context, ethics, and safety responsibility. In the field of engineering, it means that while AI can help with repetitive tasks such as preliminary design iterations, code compliance checks, or standard simulation runs, there are still certain tasks that require human expertise, like those involving context, ethics, and safety considerations. In engineering entrepreneurship settings, AI is becoming an opportunity generator, an enabler for innovation-led entrepreneurship, and a tool for entrepreneurial skill development for engineering graduates [26].

The framing of AI and the future of work by Ernst et al. highlights that research so far has focused on net job gains and losses rather than on changes in job quality, working hours, labour relations, and the overall societal impacts of AI adoption, such as the environmental cost [27]. This wider scope is directly applicable to engineering organisations: the adoption of AI has implications for the number of engineers required; the organisation of engineering work; supervision and assessment of engineering work; and the distribution of responsibility between human and automated practitioners.

4.2. Engineering Education and Human-Centered Design

To be effective in addressing the societal impact of AI, a proactive "design stance" is needed that brings ethical, legal and reflective skills into the fold of engineering education, not as a secondary concern, but as a fundamental component of the technical curriculum [4]. In the realm of higher education, empirical findings indicate that the use of AI in education, such as in digital libraries and knowledge access systems, can augment the resources available to learners and empower them to engage with learning on their own terms in the context of engineering education [28–30]. Furthermore, industry-oriented training and structured placement schemes are still essential to ensure that engineering graduates have the necessary adaptability skills for AI-supported industrial settings [31].

This involves training engineers to critically evaluate the output of models, as well as understanding the constraints of training data and conveying uncertainty about AI to non-technical audiences. These are becoming more commonly regarded as essential engineering skills, and not just electives, because the engineer's traditional duty of care now has to encompass the systems that support, but don't supplant, professional judgment [1,24].

4.3. Equity and Differential Exposure

AI has a disproportionate impact on society as an engineering phenomenon. More extensive analyses of the labor market suggest that the impact of AI-induced change is not uniform across all workers, with certain groups more likely to benefit from increased productivity through AI than others [27]. In engineering, it is likely that the companies and public institutions that have more access to data infrastructure, computational resources, and specialized skills will be quicker at adopting AI than smaller companies or those in remote areas, thus triggering concerns about the competitive and development gap that engineering institutions and professional bodies will have to bridge by training, certifying, and providing equitable access to tools [32]. Figure 3 illustrates the impact of AI-driven automation on engineering, including the development of new skills, education, productivity, and the ways in which humans and AI will work together. Figure 3 depicts the implications of AI-driven automation in engineering, its influence on skills development, education, productivity, and human-AI collaboration, and the challenges of workforce displacement, inequity, and digital inclusion.

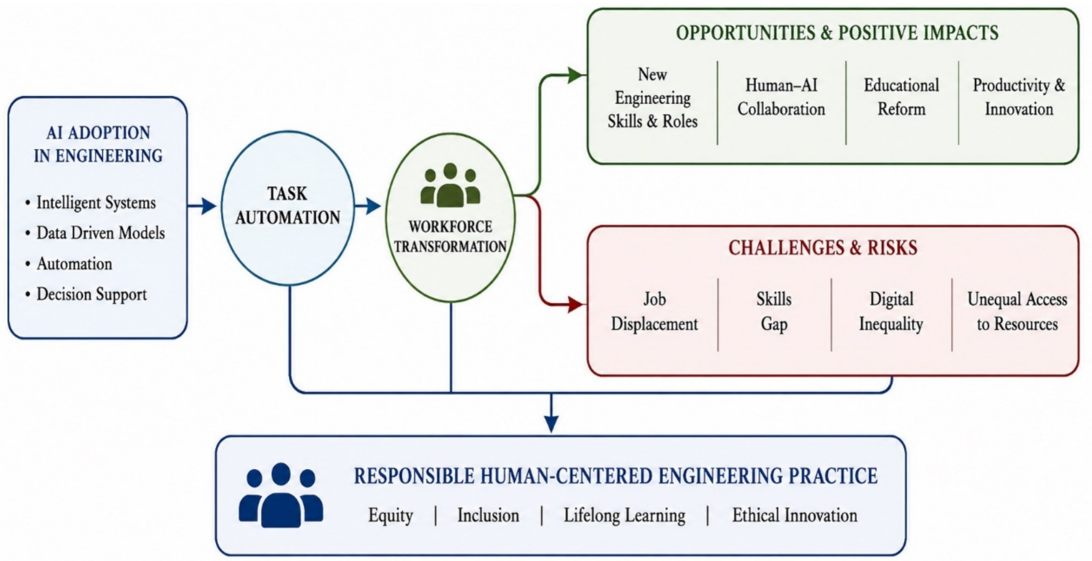

Figure 3. Societal Transformation Pathways of AI in Engineering.

5. Environmental Sustainability: AI as Enabler and as Burden

5.1. AI as an Enabler of Sustainable Engineering

A substantial body of evidence documents AI's contribution to environmental sustainability across engineering domains. In renewable-energy systems, AI techniques improve forecasting of variable generation, optimize storage dispatch, and enhance grid stability, supporting higher penetration of solar and wind power [33]. In emerging energy transition frameworks, AI combined with distributed ledger technologies such as blockchain is being explored to enable decentralized energy trading systems that improve transparency, efficiency, and renewable energy integration [34].

In the built environment, AI integrated with building information modeling (BIM) supports energy-efficient design and operation of buildings within smart-city contexts, while AI-enabled frameworks for construction and demolition waste management improve material recovery and reduce landfill burden [35,36]. Digital-twin technologies combined with AI further enable continuous, data-driven environmental planning for sustainable smart cities, allowing infrastructure operators to simulate and optimize resource flows before committing to costly physical interventions [37].

Toderas's systematic review of AI for sustainability synthesizes this evidence across the Sustainable Development Goals, concluding that AI offers genuine and measurable contributions to climate action, resource management, and net-zero objectives, while cautioning that these benefits are neither automatic nor free of risk [38].

5.2. AI's Own Environmental Footprint

AI's computing infrastructure comes with a not insignificant environmental price. Large models require a significant amount of electricity to train and run; recent empirical studies of the power consumption of single nodes during AI training on modern GPU systems directly measure this power consumption at the hardware level, highlighting the costs of training and operating these large models [39]. Schwartz and his colleagues' seminal "Green AI" argument advocates for the field to report and minimize computational cost as a first-class research goal, along with accuracy, and not as an ancillary byproduct of efficiency [7]. More recent critical perspectives go further, suggesting that efficiency gains are not enough to ensure environmentally sustainable AI, as lower cost and greater efficiency often lead to greater demand for AI services, a rebound effect that is often described in the context of the Jevons paradox [8,12] whereby the more efficient the computation, the greater the aggregate energy consumption.

This tension is especially striking in engineering applications involving large-scale models, like network optimization and simulations of infrastructure. The challenge of coordinating the optimization of low-carbon energy and information networks using AI is a two-sided issue: it involves balancing the carbon emissions generated by the training, deployment, and hardware life cycles of AI models with the emissions reductions that the optimization of other components of the system can achieve [33]. Huang and Gopal's cross-disciplinary analysis of Green AI also emphasizes the need to scale up the integration of renewable energy into AI infrastructure, create global regulations for the ecological footprint of AI, and raise public and professional awareness of the resource costs of AI [6].

5.3. Towards Life-Cycle Environmental Accountability

In engineering practice, the results indicate that environmental sustainability analyses of AI-enabled systems should not only consider the operational cost savings that an AI application brings, but also the embodied energy, water consumption, and emissions from the AI system itself, throughout its life cycle from manufacturing to training, deployment, and eventual decommissioning [11,12]. This life-cycle approach is similar to the approach used in engineering practices for environmental impact assessment and life-cycle analysis, and it is suggested that current engineering methodologies should be applied to AI systems, and not that AI is exempt from the sustainability accounting practices of engineering.

6. Towards an Integrated Framework for Responsible AI Engineering

As shown in the previous sections, ethical governance, societal transformation and environmental sustainability are not distinct aspects of the transition, but are rather all interconnected. This review suggests that there are three intertwined commitments for responsible AI engineering. Explainability and accountability should be considered as design requirements, rather than as afterthoughts: engineering organizations should follow the XAI methods and documentation practices in accordance with the risk tier of the application, as per the emerging regulatory requirements under instruments like the EU AI Act [2,3,15]. In addition, workforce and educational approaches need to prepare for the transformation of tasks and not simply job numbers, incorporating ethical and interpretive skills into engineering education and continuing education to enable practitioners to effectively oversee and guide, not simply accept, AI-generated outputs [4,5]. Additionally, environmental accounting for AI-powered engineering systems should be done on a full life-cycle basis, accounting for the embodied computational footprint of the AI systems that create the sustainability gains, and explicitly accounting for rebound effects that may offset the gains [7,12].

These three pledges are reinforcing each other. Transparent governance creates trust among the public and professionals that AI-supported sustainability interventions are effective, a workforce that can spot when recommendations clash with sustainability or safety goals, and a basis for evidence that regulators and professional bodies can use to evolve governance requirements over time. As with previous transitions in engineering practice and standards, engineering institutions, accrediting agencies, and professional societies thus have a key role to play in the implementation of this integrated system [11,24]. Figure 4 shows the intersection of ethical governance, societal responsibility, and environmental sustainability, and how they all contribute to a trustworthy, human-centric, and sustainable AI-enabled engineering system.

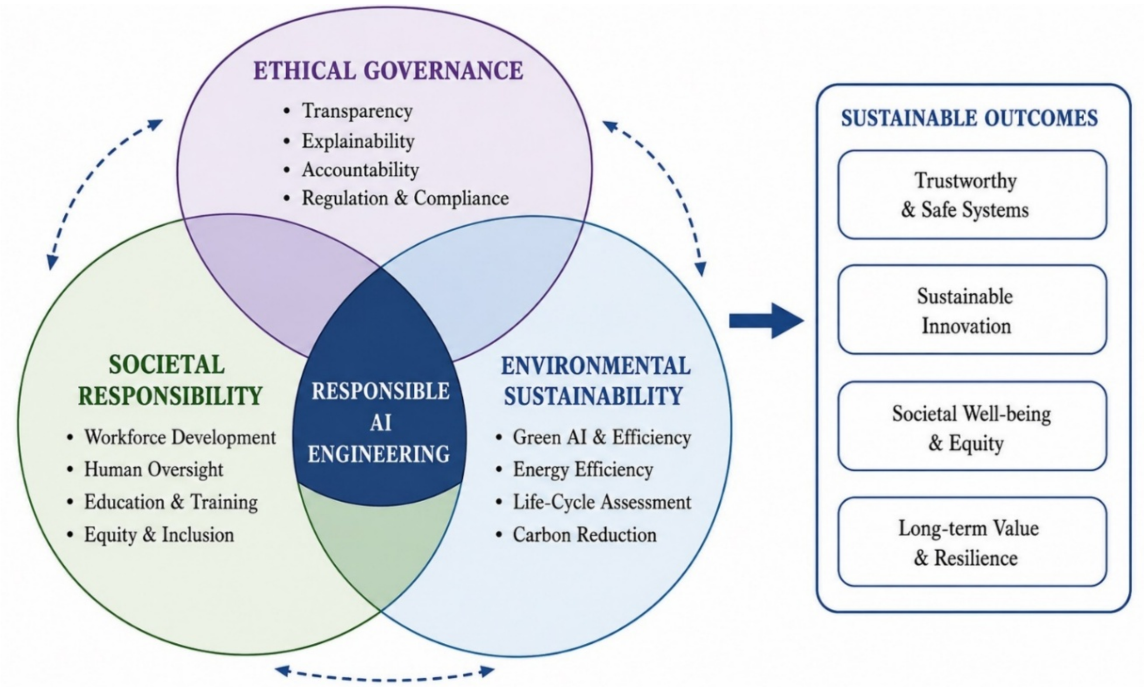

Figure 4. Integrated Framework for Responsible AI Engineering.

7. Challenges and Future Research Directions

An integrated framework is tempered with a number of challenges. First, there is no consensus on evaluation standards for explainability techniques, and they are not unified, making it difficult to require explainability in regulation without defining which techniques meet this requirement [21]. Second, governance instruments like the EU AI Act are still at the early stages of implementation, and their impact on engineering practice in the real world, especially beyond the EU, is unclear and should be explored over time [15]. Third, there is a lack of transparency in the energy and water use of AI systems from the providers of AI hardware and cloud services, and it is difficult to conduct independent life-cycle assessment [6,10]. Fourth, it is not yet fully understood how the use of AI is distributed by size of engineering firm and by region of the country that has access to computational infrastructure, and this is a priority for future empirical research [27].

Empirical, cross-disciplinary research that collectively measures the ethical, societal, and environmental performance of specific AI-enabled engineering systems should be prioritised for future work, rather than research that considers these dimensions separately. This would make a significant contribution to bridging the gap between aspirational governance principles and verified engineering outcomes as AI becomes more widely adopted in engineering practice [14,16,19].

8. Conclusions

AI is becoming an integral part of how engineered systems are designed, monitored, and maintained. The review has revealed that the legitimacy and long-term benefits of this transition will be contingent on three mutually reinforcing commitments: to govern AI transparently and with responsibility; to manage the societal impacts of AI on the engineering workforce and decision-making authority fairly; and to keep the environmental impacts of AI within the same sustainability principles that engineering follows when developing systems. All these commitments cannot be realised through technical solutions alone; they all depend on the institutional engagement of engineering educators, professional bodies, regulators and practitioners. In the future, engineering will be poised to drive, not just react to, this transformation, with its strong history of safety accountability, life-cycle thinking, and the public-interest obligation. To realize that potential will necessitate a rethinking of how ethical governance, societal impact, and environmental sustainability are treated as limitations on AI-enabled engineering, and how the success of AI-enabled engineering is measured by the extent to which it achieves those goals.

Funding

This research received no external funding.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

This manuscript is a review, and no novel experimental data, raw datasets or samples were generated during the preparation of this paper. All information and evidence discussed in this work derive from previously published studies listed in the reference section. All cited publications are publicly accessible.

Conflicts of Interest

The author declares no conflict of interest.

Use of AI and AI-Assisted Technologies

During the preparation of this work, the author used Gemini 3.0 Pro to perform grammar and spelling checks. After using this tool, the author reviewed and edited the content as needed and takes full responsibility for the content of the published article.

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