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# Towards Sustainability of AI: Organizational Adaptation for Environmentally Responsible Systems

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## Abstract

Artificial Intelligence (AI) has emerged as one of the most transformative technological advancements of the 21st century, revolutionizing industries ranging from healthcare and finance to logistics and education. However, this rapid growth is accompanied by significant environmental challenges, particularly in terms of energy consumption and greenhouse gas emissions. The AI lifecycle encompassing data acquisition, model training, deployment, and inference contributes to substantial ecological footprints, highlighting an urgent need for sustainable development principles to be integrated into AI design and deployment.

This paper explores the dual dimensions of sustainable AI: *AI for Sustainability* and *Sustainability of AI*. The former focuses on leveraging AI technologies to address environmental challenges and advance the United Nations' Sustainable Development Goals (SDGs), while the latter addresses the environmental costs associated with AI systems themselves, including high energy consumption, inadequate lifecycle models, and fragmented regulatory frameworks.

Through a qualitative and quantitative analysis of existing literature and case studies, this paper identifies key solutions to mitigate these impacts. These include developing energy-efficient AI hardware such as Neural Processing Units (NPUs), embedding sustainability principles across every stage of the AI lifecycle, and fostering cross-sector collaborations to establish standardized regulatory frameworks. For instance, Kneron Inc. has demonstrated that optimizing AI-specific hardware can reduce energy consumption by approximately 30%, offering a viable model for energy efficiency in AI deployment.

The study concludes that achieving sustainable AI requires simultaneous technological, organizational, and legislative adjustments. Sustainability must not be treated as an afterthought but rather as a foundational principle for AI innovation. By prioritizing environmental considerations, AI systems can evolve into tools that drive progress without compromising the planet's ecological balance.

**Keywords:** ***Sustainable Artificial Intelligence (AI), Energy Efficiency, Lifecycle Assessment (LCA), Neural Processing Units (NPUs), AI Carbon Footprint, Cross-Sector Collaboration, Regulatory Frameworks.***

## 1.0 Introduction

Artificial Intelligence (AI) is now considered an indispensable element of technological advancement, fundamentally transforming industries including healthcare, finance, and even the broader social structure. However, this rapid proliferation has raised significant environmental concerns. The launch of ChatGPT in November 2022, for instance, spurred a surge in AI investment, development, and deployment, but simultaneously escalated energy consumption and carbon emissions (Goldman Sachs, 2024). As computational demands continue to rise exponentially, there is a pressing need to better understand how AI systems can align with sustainable development goals and address environmental aspirations set forth by the United Nations.

The sustainability discourse around AI can be categorized into two primary branches: *AI for Sustainability* and *Sustainability of AI* (Van Wynsberghe, 2021). The former concerns the application of AI in tackling critical environmental challenges, optimizing resource usage, and supporting the Sustainable Development Goals (SDGs). The latter focuses on addressing the environmental costs of AI technologies themselves, including energy consumption, carbon footprints, and electronic waste. This dual framework highlights a paradox: while AI holds immense potential for driving sustainability initiatives, its rapid expansion also intensifies humanity's environmental footprint (Alzoubi and Mishra, 2024; Naeeni and Nouhi, 2023).

The environmental impacts of AI are primarily rooted in its high energy consumption. Training machine learning models, particularly deep learning algorithms, demands significant computational power. For instance, training a single Natural Language Processing (NLP) model can emit greenhouse gases equivalent to the lifetime emissions of five average cars (Strubell et al., 2020). Furthermore, computational demands for AI systems are now doubling every two months, outpacing Moore's Law, which traditionally predicted a doubling every two years (Goldman Sachs, 2024). This accelerating demand necessitates more energy-efficient architectures, as traditional CPUs and GPUs remain suboptimal for AI workloads, leading to inefficiencies during both the training and inference phases (Basharat, 2022).

However, the challenges extend beyond hardware limitations. Organizational barriers, including poor lifecycle assessment, lack of standardized documentation, and fragmented policies, pose significant obstacles to achieving sustainability in AI (Prasad Agrawal, 2023; Rohde et al., 2024). Frameworks such as the Life Cycle Screening of Emerging Technologies (LiSET) and Life Cycle Assessment (LCA) have been proposed to evaluate environmental impacts during early stages of technological adoption (Hung et al., 2018; Thenemann et al., 2020). Yet, these frameworks often lack cultural and organizational adaptability, rendering them less effective in influencing sustainable practices.

Policy gaps further compound these challenges. Current regulations are typically generalized and fail to address the unique environmental concerns posed by AI systems. Voluntary initiatives, such as the Artificial Intelligence Environmental Impacts Act of 2024, have achieved limited success due to insufficient enforcement and lack of cross-sectoral collaboration (Perucica & Andjelkovic, 2022; Kulkov et al., 2024). Without harmonized regulatory frameworks, efforts to minimize AI's ecological footprint remain fragmented and inconsistent.

Addressing these issues requires a multi-faceted approach. Technological advancements, such as specialized Neural Processing Units (NPUs) designed for AI workloads, offer promising solutions for improving energy efficiency (Hudaszek et al., 2023). Equally important are holistic lifecycle management practices and robust policy interventions aimed at ensuring accountability and standardization across the AI ecosystem.

Ultimately, the integration of sustainability principles into AI development is not merely an engineering challenge but a societal responsibility. Achieving sustainable AI necessitates coordinated efforts across technological, organizational, and legislative dimensions. This paper seeks to examine these challenges, propose actionable solutions, and present a comprehensive framework for embedding sustainability into every stage of the AI lifecycle. By doing so, it aims to ensure that AI continues to thrive as an innovative technology while respecting the planet's ecological limits.

## 2.0 Literature Review

This literature review focuses on the environmental concerns of AI while also assessing frameworks and strategies regarding those concerns. This section is organized into three key areas: the high energy consumption of AI, the limitations of AI lifecycle frameworks, and the lack of comprehensive regulations and standards.

### 2.1 Energy-Intensive Nature of AI

AI is increasingly being adopted in the market, and its pace has caused an exponential performance and impact on energy consumption and the environment. Strubell et al. (2020) pointed out that one training of an artificial intelligence model leads to the emission of approximately 600,000 pounds of carbon dioxide. This amount is equal to five lifetime emissions of a car each. AI has required exponentially more computational resources based on the amount of data, and the requirement has been rising at a month, with no sign of slowing down since mid-2018, compared to Moore’s rate of every two years (Goldman Sachs, 2024).

Energy inefficiency is evident in both training and inference phases of the neural network. Training is a computationally heavy process, performed on a large dataset, whereas the second phase, called inference as well, requires a significant amount of energy (El-Khattab & Fathy, 2023). This is made worse by the dependence on general-purpose CPUs and GPUs since these hardware systems are not designed to offer optimal AI results and hence consume additional power that is not actually needed (Basharat, 2022).

Remedial actions towards the realization of energy efficient hardware have been embarked on. Yokoyama et al. (2023) underlined the importance of green AI undertakings with regards to the energy consumption of the machine learning frameworks. Another example is a startup Kneron Inc. that proposed to create NPUs, which are task-specific AI chips that consume much less power compared to traditional processors while being almost as efficient. Moving to such specific devices could help organizations reduce energy consumption dramatically, which points to the effectiveness of the technological approaches to tackle AI’s sustainability issue.

### 2.2 Life Cycle Framework for AI Sustainability

The adoption of lifecycle assessment (LCA) frameworks has emerged as a key method for embedding sustainability into both the development of AI technologies and their responsible usage. These frameworks are designed to evaluate the environmental implications of a product or technology throughout its entire life cycle. The Life Cycle Screening of Emerging Technologies (LiSET), developed by Hung et al. (2020), aims to enable developers to conduct an early assessment of the sustainability impacts that may arise when innovative technologies are scaled for widespread application.

Similarly, Thenemann et al. (2020) provided guidance on performing prospective life cycle assessments for disruptive technologies, emphasizing the integration of sustainability into the initial design stages. These frameworks equip organizations with tools to pinpoint critical areas for improving efficiency, particularly in terms of energy and resource utilization, across various stages of the technology lifecycle.

However, the effectiveness of lifecycle frameworks is often hindered by organizational practices and cultures that prioritize performance metrics and rapid scalability to meet growing demands. Kulkov et al. (2024) highlighted that sustainable, collaborative, and high-quality data practices have not yet fostered an effective data culture capable of supporting the successful implementation of LCA. This oversight perpetuates unsustainable business practices and neglects the broader organizational transformations needed to align AI systems with environmental goals.

Agrawal (2023) reinforced this perspective, advocating for a more holistic approach to lifecycle management. This approach emphasizes integrating sustainability considerations not only at the outset but also throughout the later stages of building, deploying, and retiring AI models. By embedding sustainability as a core component rather than treating it as an afterthought, this approach ensures that environmental considerations are deeply integrated into the AI development lifecycle.

### 2.3 Deficiencies in Guideline and Norm Making

The absence of stabilized regulations and standardized norms in the artificial intelligence industry poses significant challenges to achieving sustainable AI practices. Perucica and Andjelkovic (2022) highlighted that existing policies are insufficient to adequately address the environmental impacts of AI technologies. This policy gap exacerbates AI's environmental footprint, creating inconsistencies across the industry, where some organizations prioritize efficiency while others emphasize performance.

To address these shortcomings, the *Artificial Intelligence Environmental Impacts Act of 2024* was introduced, requiring organizations to voluntarily disclose environmental metrics related to their AI usage. While this represents a step towards greater accountability, Alzoubi and Mishra (2024) argued that corporate-led initiatives alone are inadequate for driving systemic innovation. Binding norms and mandatory reporting standards are essential for ensuring sustainability is implemented at scale across the AI ecosystem.

One effective strategy for enhancing regulatory frameworks includes fostering increased cooperation among governments, industries, and academic institutions. Xiaoxi et al. (2020) emphasized the importance of standardizing AI measures in combating climate change, arguing that clear and well-defined standards are necessary to balance technological advancement with environmental preservation. Collaborative research initiatives led by universities can drive innovation in sustainable AI solutions, while industry groups serve as platforms for cross-organizational knowledge sharing and the dissemination of best practices.

### 2.4 Necessary Summary of Challenges and Opportunities

The literature identifies three critical challenges to achieving sustainable AI:

1. **Energy Consumption:** The rising computational demands of AI have resulted in significant energy consumption and an unsustainable carbon footprint. Current hardware infrastructures are insufficiently equipped to address the environmental consequences of contemporary AI applications.
2. **Lifecycle Integration:** While lifecycle frameworks provide valuable tools for assessing and mitigating environmental impacts, their effectiveness is hindered by legislative and organizational gaps. Additionally, prevailing organizational cultures often deprioritize sustainability, limiting the successful integration of these frameworks.
3. **Regulatory Gaps:** The absence of cohesive policies and standardized procedures weakens collaborative efforts aimed at reducing AI's environmental impact.

Addressing these challenges requires a multifaceted approach, including the adoption of energy-efficient hardware, embedding sustainability into lifecycle systems, and establishing robust and standardized regulatory frameworks. By integrating these strategies, the AI industry can harmonize technological advancement with environmental responsibility, paving the way for a more sustainable future.

## 3.0 Methodology

This paper employs a qualitative research design to operationalize the measure of sustainability in Artificial Intelligence through five interconnected procedures. A combination of literature reviews, case studies, frameworks, and data synthesis ensure that key aspects of sustainable AI-including organizational, technical, and policy dimensions are thoroughly examined. Below is a detailed breakdown of the methodology:

### 1. Literature Analysis

To achieve the research objectives, this study conducts a comprehensive literature review to identify gaps and barriers to sustainable AI. The review includes scholarly articles, industry reports, and policy papers, focusing on the environmental costs of AI systems and recommended solutions. The literature analysis emphasizes:

- Energy Consumption in AI Models: Strubell et al. (2020) and El-Khattab & Fathy (2023) highlight the significant energy consumption and carbon footprint of AI training and inference processes, underscoring the need for more computationally efficient models.
- Lifecycle Assessment Tools: Frameworks like LiSET (Hung et al., 2018) and Prospective LCA (Thenemann et al., 2020) provide tools for preliminary assessments of environmental impacts in emerging technologies.
- Organizational and Cultural Factors: Studies by Kulkov et al. (2024) and Prasad Agrawal (2023) identify organizational cultures and systemic barriers that hinder sustainable AI integration.
- Regulatory Voids: Perucica and Andjelkovic (2022) address the importance of regulatory standardization and interoperability in aligning AI development with environmental objectives.

### 2. Case Study Analysis

This study examines case studies of organizations and technologies recognized for environmentally sustainable AI systems.

- Kneron Inc.: Known for its energy-efficient hardware, Kneron's NPU technology demonstrates up to 1000x energy savings and 10x computational efficiency compared to standard hardware. This aligns with recommendations from Hudaszek et al. (2023) and Basharat (2022), who emphasize leveraging native architecture for energy savings.
- Hardware-Software Co-Optimization: Comparative analyses of post-ASIC and pre-ASIC AI hardware reveal differences in carbon footprints during machine learning processes. Yokoyama et al. (2023) and Xiaoxi et al. (2020) provide significant insights into the synergies between hardware and software for improved sustainability.

### 3. Framework Development

The study proposes a lifecycle framework structured around three core levels:

- **Organizational Level:** Building on Alzoubi and Mishra (2024) and Kulkov et al. (2024), this level emphasizes cultivating a data culture focused on quality, integrity, and accountability. Organizations are encouraged to enforce codes of conduct, collaborative practices, and standardized documentation to ensure sustainability goals are met.
- **AI Development Level:** Inspired by Hung et al. (2018) and Thenemann et al. (2020), this level incorporates lifecycle assessment methodologies throughout AI development. Naeeni and Nouhi (2023) recommend employing energy-efficient algorithms and model compression techniques to minimize computational load.

- **Policy and Governance Level:** This level advocates for standardization and regulatory frameworks, drawing insights from the *Artificial Intelligence Environmental Impacts Act of 2024* (Perucica and Andjelkovic, 2022). Stakeholder engagement across government, academia, and industries is promoted to ensure an integrated and policy-driven approach to AI sustainability (Thoennen et al., 2020).

**4. Cross-Sector Collaboration**

The methodology underscores the importance of cross-sector interactions involving governments, industries, and academic institutions to foster sustainable practices.

- Knowledge Sharing: Case studies and reports by Van Wynsberghe (2021) and Yokoyama et al. (2023) demonstrate how partnerships facilitate knowledge exchange, harmonization of practices, and technology development.
- Collaborative Gaps: Collaboration is particularly crucial in addressing the lack of lifecycle documentation and ensuring environmentally relevant aspects are comprehensively covered by all stakeholders.

**5. Data Collection and Synthesis**

This study synthesizes data from diverse sources, including:

- Quantitative Measures: Data on energy consumption and carbon footprints from existing AI models (Strubell et al., 2020; Goldman Sachs, 2024).
- Organizational-Level Insights: Findings on organizational strategies and regulatory measures (Alzoubi & Mishra, 2024; Prasad Agrawal, 2023).
- Emerging Technologies: Research on innovative technologies designed to reduce energy usage across hardware and software (Hudaszek et al., 2023; Xiaoxi et al., 2020).

The collected data is systematically analyzed to identify patterns, relationships, and actionable recommendations for the proposed sustainability framework.

## 4.0 Proposed Solutions and Framework

Achieving AI sustainability cannot rely solely on technical solutions; it must also be supported by organizational strategies and policy frameworks. This section outlines strategic approaches to address environmental challenges, including immediate hardware solutions, lifecycle optimization, and policy standardization. These solutions align with objectives such as efficiency, energy conservation, and cross-sector collaboration.

**1. Upgrade to Energy Efficiency Hardware**

Apple suggests that one of the most impactful ways to reduce AI's environmental footprint is by adopting energy-efficient hardware specifically designed for AI processing. Standard CPUs and GPUs are often inadequate for AI tasks, leading to significant energy consumption and reduced efficiency (Strubell et al., 2020; El-Khattab & Fathy, 2023). Specialized hardware, such as NPUs (Neural Processing Units), offers a more sustainable solution.

- Case Study of Kneron Inc.: Kneron Inc. demonstrates that AI-specific hardware can enhance energy efficiency without compromising performance. Integrating GPUs with NPUs can yield a 10-25% performance increase while reducing computational resource usage by 30% (Basharat, 2022). This mirrors earlier transitions where GPUs replaced CPUs for graphical tasks, showcasing the potential of purpose-built hardware (El-Khattab & Fathy, 2023).
- Model Compression: Techniques like model compression enable AI models to run efficiently on lightweight hardware while maintaining accuracy (Yokoyama et al., 2023). This approach reduces the carbon footprint of both the training and inference phases of AI development.

Adopting energy-efficient hardware and optimized algorithms can significantly reduce the environmental toll of AI systems during development and deployment.

**2. Holistic Lifecycle Management**

Sustainability in AI must span the entire lifecycle from inception and development to implementation and maintenance. Organizations need to cultivate environments that are both sustainable and productive.

- Lifecycle Assessments (LCA): Tools such as LiSET and LCA enable early-stage evaluation of environmental impacts. These tools guide resource optimization, minimize waste, and identify key areas for improvement in production processes (Hung et al., 2018; Thenemann et al., 2020). However, traditional LCA approaches often overlook organizational decision-making and staff engagement, which are crucial for achieving long-term sustainability goals (Kulkov et al., 2024).
- Data Culture and Integrity: Organizations must prioritize data integrity and quality assurance to prevent redundancies and improve efficiency. Proper documentation, adherence to standards, and a commitment to transparency create systems that are both efficient and environmentally friendly (Rohde et al., 2024).

Applying circular thinking and lifecycle assessments across all AI development phases ensures alignment with both environmental goals and operational efficiency.

**3. Policy and Regulatory Standardization**

The absence of coherent regulatory frameworks is a significant barrier to achieving sustainable AI. Without clear guidelines, organizations often prioritize performance metrics over environmental stewardship, leading to inconsistent practices across industries (Perucica & Andjelkovic, 2022).

- Need for Unified Regulations: Policies such as the Artificial Intelligence Environmental Impacts Act of 2024 have mandated voluntary reporting of environmental metrics related to AI usage. However, mandatory standards are essential to ensure widespread compliance and alignment with sustainability goals (Perucica & Andjelkovic, 2022).

- Cross-Sector Collaboration: Effective policy implementation requires cooperation between governments, academia, and industries. Partnerships with academic institutions can drive innovation in energy-efficient algorithms, while government oversight can enforce compliance through mandatory carbon footprint declarations (Kulkov et al., 2024; Xiaoxi et al., 2020).

Standardizing regulatory policies will enhance compatibility across sectors and foster collective progress towards an environmentally sustainable AI ecosystem.

**4. Intersectoral Cooperation for Accountability**

A siloed approach to AI development has hindered progress towards sustainability. Technological advancements are typically driven by private companies, while public institutions focus on application, and academic researchers handle theoretical advancements. Bridging these silos is critical for creating holistic sustainability strategies.

- Sharing Tools and Research: Collaborative alliances facilitate the exchange of best practices, tools, and knowledge benchmarks. This prevents redundant efforts and accelerates the adoption of innovative solutions (Naeeni & Nouhi, 2023; Alzoubi & Mishra, 2024).
- Joint Policy Development: Cooperative frameworks help develop shared guidelines that balance innovation with sustainability goals. Industry consortia, such as eco-chip initiatives, demonstrate how shared corporate responsibility can drive meaningful environmental outcomes (Thonemann et al., 2020; Hudaszek et al., 2023).

Cross-sectoral collaboration ensures that all stakeholders technology developers, regulators, and environmental organizations align their efforts towards a cohesive and globally recognized sustainability standard.

**Summary of Proposed Framework**

The proposed solutions emphasize a multi-tiered approach:

**1. Technical Level:**

- Succession of the use of energy-efficient hardware such as NPUs.
- Application of model compression to cut down energy consumption.

**2. Organizational Level:**

- Promote the culture where data is accurate, complete and systematic.
- Use tools such as LiSET that analyses a product's life cycle and determine points that negatively affect the environment.

**3. Policy Level:**

- The final policy recommendations include: Support binding secondary rules, and mandatory reporting of carbon emissions.
- Demonstrate and encourage interorganizational resource and knowledge exchange.

When these solutions are incorporated, the sustainability of AI can be achieved to allow for its growth to be in a sustainable way.

## 5.0 Results

The analysis highlights key findings across energy efficiency, lifecycle integration, standardization deficiencies, and cross-industry collaboration regarding the environmental sustainability of AI systems. These findings identify practical challenges associated with AI's environmental impact and propose viable technological and strategic solutions.

**1. Energy Efficiency through Specialized Hardware**

A major concern in AI systems is their energy consumption during the training and inference phases. Strubell et al. (2020) estimated that training a single NLP model produces 600,000 pounds of $CO_2$ emissions, equivalent to the lifetime emissions of five cars. This highlights the substantial carbon intensity associated with AI's computational demands.

Energy-efficient hardware has emerged as a key solution to address these challenges. One notable advancement is the development of reconfigurable Neural Processing Units (NPUs) by Kneron Inc., specifically optimized for AI tasks. These NPUs reduce computational power consumption by 30% while delivering a 10-25% increase in performance compared to traditional GPUs and CPUs (Basharat, 2022; Hudaszek et al., 2023). This shift allows legacy hardware to focus on general computational throughput, improving overall system efficiency.

The exponential growth in AI's computational demands, with AI power expected to double every two months by 2024 (Goldman Sachs Research), underscores the urgency for hardware advancements. Transitioning from generic hardware to AI-specific hardware architectures is critical for balancing energy consumption with high performance levels (El-Khattab & Fathy, 2023). This evolution mirrors previous paradigm shifts in computing, such as the adoption of GPUs for graphical processing.

**2. Approaches for Sustainable Integration of Lifecycle in AI Development**

Sustainability must be embedded throughout the AI lifecycle from development and deployment to maintenance and eventual decommissioning. Tools like Life Cycle Assessment (LCA) and Life Cycle Screening of Emerging Technologies (LiSET) are instrumental in identifying environmental impacts early in AI development (Hung et al., 2020; Thenemann et al., 2020). These frameworks enable better resource utilization, minimize waste, and optimize energy consumption throughout the AI lifecycle.

However, adoption of these frameworks remains limited. Many organizations neglect lifecycle sustainability principles, resulting in inefficient processes and heightened energy usage. Rohde et al. (2024) emphasize the need to foster organizational cultures centered on data quality and integrity. Sustainability must become an intrinsic part of innovation rather than an afterthought.

Incorporating cyclical design loops, minimizing redundant processes, and reducing energy use during both training and inference phases can significantly enhance lifecycle sustainability (Kulkov et al., 2024). Organizations that successfully apply these frameworks demonstrate stronger alignment between business operations and environmental objectives. Well-documented workflows, optimized algorithms, and streamlined operations contribute to minimizing energy consumption without compromising performance.

**3. Standardization and Policy Gaps**

The absence of standardized regulatory frameworks poses a significant challenge to sustainable AI development. Current environmental policies are often fragmented and fail to offer tailor-made solutions for AI technologies (Perucica & Andjelkovic, 2022). This lack of uniform regulations results in inconsistencies across industries, where some organizations prioritize performance metrics over energy efficiency.

The *Artificial Intelligence Environmental Impacts Act of 2024* seeks to address these shortcomings by introducing voluntary reporting systems for AI-related environmental impacts. However, these measures lack enforcement mechanisms to drive widespread adoption. Yokoyama et al. (2023) advocate for mandatory reporting requirements aligned with TCFD (Task Force on Climate-related Financial Disclosures) standards to create collective accountability among companies.

The lack of cross-industry standardization also hinders proactive collaboration. Regulatory gaps prevent industries, academia, and public institutions from sharing resources, knowledge, and best practices effectively. Establishing comprehensive regulatory policies will ensure that AI innovation aligns with environmental sustainability objectives across all sectors.

**4. Learning from other sectors and adopting best practice in a more polarized system**

Technology leaders, academic institutions, and policymakers must engage in mutual cooperation to create effective sustainability strategies.

- Academic Contributions: Partnerships with academic institutions have driven advancements in energy-efficient algorithms and hardware technologies.
- Policy Alignment: Collaboration with standard-setting agencies ensures that environmental policies address the specific needs of AI systems (Naeeni & Nouhi, 2023; Alzoubi & Mishra, 2024).

Organizations engaged in cross-sector initiatives report higher success rates in implementing sustainable practices. Industry consortia facilitate the sharing of tools, research insights, and benchmarks, accelerating the adoption of green hardware and software solutions (El-Khattab & Fathy, 2023).

Intentional frameworks that promote accountability and transparency, such as emission reporting guidelines and usage optimization frameworks, further support sustainability goals. Partnerships between governments, environmental organizations, and academic researchers can ensure that technological advancements align with global sustainability initiatives.

## 6.0 Discussion

The findings of this study highlight the complex interplay of factors influencing the sustainability of artificial intelligence (AI). While AI offers transformative opportunities across multiple fields, its environmental footprint during development and deployment has become a pressing global concern. This section synthesizes the key findings, emphasizing the systemic changes required in hardware adoption, organizational culture, and regulatory frameworks to achieve sustainable AI.

**6.1 Increase Use of Energy Efficient Hardware**

A key insight from this study reveals that AI systems can become significantly greener through energy-efficient hardware solutions. Technologies such as Neural Processing Units (NPUs), like those developed by Kneron Inc., demonstrate how specialized hardware can optimize AI performance. These NPUs reduce power consumption by 30% while achieving a 10-25% performance increase compared to traditional CPUs and GPUs (Basharat, 2022).

However, despite these advancements, widespread adoption remains limited due to high transition costs and organizational inertia (El-Khattab & Fathy, 2023). Previous technological shifts such as the transition from CPUs to GPUs for graphical processing illustrate that such adoption is not only possible but necessary. For AI to experience similar momentum, industry stakeholders must prioritize investments in AI-specific hardware and align efforts across sectors (Hung et al., 2020).

Additionally, techniques like model compression and algorithm optimization must complement hardware efficiency, ensuring that AI systems remain both high-performing and environmentally conscious.

**6.2 Integration of Sustainability into the AI Lifecycle**

Sustainability must be embedded throughout the AI lifecycle, from development and deployment to maintenance and eventual decommissioning. Frameworks such as Life Cycle Assessment (LCA) and Life Cycle Screening of Emerging Technologies (LiSET) offer valuable tools for evaluating environmental impacts at early development stages (Hung et al., 2020; Thenemann et al., 2020).

However, adoption of these frameworks remains inconsistent and limited to technical aspects, often excluding organizational and cultural factors. Organizations prioritizing scalability over sustainability tend to amplify resource consumption and environmental strain (Naeeni & Nouhi, 2023), which escalate energy and resource consumption (Naeeni & Nouhi, 2023).

Closing these gaps requires integrating sustainability into organizational culture and processes. This involves:

- Maintaining data integrity and quality standards.
- Enhancing documentation processes.
- Aligning environmental goals with short-term business objectives.

By fostering an organizational culture that values sustainability, companies can create prevention-based design strategies that align AI development with long-term ecological resilience (Kulkov et al., 2024; Boons, 2018; Steidel-Moreno et al., 2020).

**6.3 Intersectoral Work and Cooperation**

The notion of reaching sustainability in AI is therefore not an issue that can posed and solved at individual organization level; it will have to be an enterprise of the different sectors. Research and innovation in sustainable AI demand the collaboration of technology stakeholders, knowledge institutions, and government institutions. For instance, the universities can work on the creation of new energy efficient algorithms, whereas the industry consortia may help to share the tools and expertise (Xiaoxi et al., 2020). In addition, partnerships with environmental organizations can help to achieve further AI development meeting the goals of environmental responsibility.

They also play a key role in addressing the economic challenges associated with practicing sustainable development. Collaboration has the potential to reduce costs and accelerate the transition to energy-efficient technologies in industries and buildings. Furthermore, there is potential for collaboration to advocate for standardized policies that promote sustainability as a collective social responsibility rather than placing the burden solely on individual accountability.

## 7.0 Conclusion

The rapid proliferation of artificial intelligence (AI) technologies presents a paradox: while AI drives innovation and societal progress, it simultaneously poses a significant threat to environmental sustainability. This duality underscores the necessity of embedding environmental responsibility at every stage of AI development and deployment. Achieving sustainable AI is not a challenge that can be solved through technological advancements alone it requires a multifaceted approach encompassing technological innovation, organizational transformation, and robust policy frameworks.

### 7.1 Addressing Energy Consumption

One of the central challenges remains the high energy consumption associated with AI systems, particularly during training and inference phases. Strubell et al. (2020) highlight the immense carbon footprint generated by training large AI models, a concern exacerbated by rising computational demands. Transitioning to energy-efficient hardware such as Neural Processing Units (NPUs) has proven effective in addressing these concerns. Companies like Kneron Inc. demonstrate how NPUs can reduce power consumption by 30% while simultaneously increasing performance by 10-25% (Hung et al., 2018; Basharat, 2022). These advancements mirror previous paradigm shifts in computing, such as the adoption of Graphics Processing Units (GPUs) for specialized tasks. To scale these improvements, industry stakeholders must prioritize investments in AI-specific hardware, complemented by model compression techniques and algorithm optimization to maximize efficiency and minimize energy waste.

### 7.2 Lifecycle Integration and Organizational Culture

Sustainability must be embedded across the entire AI lifecycle, from design and development to deployment and decommissioning. Tools such as Life Cycle Assessment (LCA) and Life Cycle Screening of Emerging Technologies (LiSET) provide frameworks for early-stage evaluation of environmental impacts (Thenemann et al., 2020; Hung et al., 2018).

However, these methodologies often fail to address organizational and cultural dimensions, limiting their overall impact. As Kulkov et al. (2024) suggest, corporate sustainability practices must focus on:

- Data integrity and accuracy.
- Efficient resource management across supply chains.
- Product returnability, reusability, and recyclability.

Building an organizational culture that values sustainability alongside productivity ensures that AI systems align with both environmental objectives and business goals.

### 7.3 Addressing Policy and Regulation Gaps

A significant barrier to sustainable AI lies in the lack of cohesive regulations and standardized policies. Current environmental policies are fragmented and inadequate, failing to account for the unique environmental implications of AI technologies (Perucica & Andjelkovic, 2022). *The Artificial Intelligence Environmental Impacts Act of 2024* offers a promising foundation, advocating for voluntary reporting and environmental accountability. However, its impact remains limited without mandatory enforcement mechanisms. Yokoyama et al. (2023) argue for the adoption of mandatory carbon emission disclosures and the creation of standardized reporting frameworks to foster collective accountability. Additionally, policy standardization must address energy consumption benchmarks, data exchange practices, and lifecycle assessments, ensuring alignment across industries and reducing regulatory disparities (Alzoubi & Mishra, 2024).

### 7.4 Intersectoral Collaboration for Sustainability

The path to sustainable AI cannot be achieved by individual organizations in isolation it demands cross-sector collaboration involving technology providers, governments, academia, and environmental organizations.

- Research Contributions: Academic institutions can pioneer energy-efficient AI algorithms and innovative sustainability solutions (Xiaoxi et al., 2020).
- Industry Consortia: Collaborative industry networks facilitate tool-sharing, knowledge exchange, and the adoption of green hardware and software solutions (El-Khattab & Fathy, 2023).
- Environmental Advocacy: Partnerships with environmental organizations ensure that sustainability goals remain central to AI advancements.

Intersectoral cooperation streamlines resources, reduces costs, and accelerates the adoption of sustainability-focused AI practices.

### A Call to Action

Achieving sustainable AI requires a systemic approach that engages all stakeholders in the AI value chain. This includes:

- **Adopting Energy-Efficient Technologies:** Prioritizing specialized AI hardware and optimizing algorithms to minimize energy use.
- **Embedding Sustainability into Organizational Practices**: Cultivating a culture of sustainability awareness, maintaining lifecycle accountability, and aligning business goals with environmental responsibility.
- **Strengthening Policy and Regulation:** Implementing standardized policies and enforcement mechanisms to ensure transparency, accountability, and collective action across sectors.

By integrating these approaches, AI can evolve as an enabler of sustainable development, balancing innovation with environmental stewardship.

The alignment of energy efficiency, lifecycle management, regulatory robustness, and cross-sector collaboration will pave the way for a sustainable AI ecosystem. As emphasized by Alzoubi and Mishra (2024), achieving this vision requires collective commitment from governments, industries, academia, and civil society worldwide.

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