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Towards Sustainable AI: Green Accounting-Based Model for Measuring the Environmental Cost of Intelligent Systems

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Abstract

The rapid growth of artificial intelligence (AI) has raised questions about its environmental, social, and economic sustainability. This study investigates the influence of three critical factors environmental impact of AI, e-waste and lifecycle implications, and green accounting practices on the development of sustainable AI in Bangladesh. Data were collected through a structured survey and analyzed using structural equation modeling (SEM) with AMOS. The results show that all three constructs significantly predict sustainable AI, with green accounting practices exerting the strongest influence ($\beta = 0.41$), followed by environmental impact ($\beta = 0.32$) and e-waste considerations ($\beta = 0.27$). Together, these predictors explain 65 percent of the variance in sustainable AI, highlighting their collective importance. The findings suggest that addressing energy use and carbon emissions, managing e-waste responsibly, and institutionalizing green accounting are essential steps for promoting sustainable AI. From a theoretical perspective, the study extends sustainability and accounting frameworks into the AI domain. From a practical perspective, it offers guidance for policymakers, industry leaders, and organizations in developing economies. The results contribute to the global discussion on responsible AI by providing empirical evidence from the context of Bangladesh

Keywords: Sustainable AI, Environmental Impact, E-Waste, Green Accounting, Structural Equation Modeling, Bangladesh

Introduction

Artificial Intelligence (AI) is increasingly embedded in daily life, shaping industries, economies, and governance worldwide. From generative language models to AI-driven agriculture and fintech solutions, the technology is considered a cornerstone of the Fourth Industrial

Revolution. However, this rapid growth has raised concerns about AI's environmental sustainability. AI systems, particularly large-scale machine learning models, demand extensive computational power and infrastructure. Their training and inference processes require significant energy, emit considerable greenhouse gases, and consume vast amounts of water for cooling purposes (Jegham et al., 2025). Projections suggest that global data centers largely powered by AI workloads could account for up to 12 percent of U.S. electricity consumption by 2028, raising serious questions about the balance between technological advancement and environmental responsibility (Time, 2025; Washington Post, 2025).

Recent disclosures by major technology firms highlight these challenges. Google, for instance, reported a 51 percent increase in overall carbon emissions between 2019 and 2024, primarily due to the expanding electricity demand of AI operations (The Guardian, 2025). Even though Google has achieved efficiency improvements such as a 33-fold reduction in energy per AI prompt usage at scale offsets such gains (Tom's Guide, 2025). These patterns reflect the Jevons Paradox, whereby improvements in efficiency lead to greater total consumption (York & McGee, 2017). As AI adoption accelerates, the cumulative impact of millions of small-scale queries and large-scale model training continues to expand the sector's ecological footprint. To address these challenges, scholars and practitioners are increasingly turning to green accounting, a sustainability-oriented extension of conventional accounting. Green accounting integrates environmental costs such as energy use, carbon emissions, and e-waste into organizational reporting and decision-making (Schaltegger & Burritt, 2018). Its application has demonstrated positive outcomes in traditional sectors, improving energy efficiency, environmental performance, and corporate accountability (Rahman et al., 2023). To maintain consistent performance growth, many firms require substantial operating capital. Unfortunately, not all have access to such resources, leading to repeated funding shortages and financial emergencies during the fiscal year (Bhattacharjee & Juman, 2023).Yet, within AI and ICT-intensive industries, green accounting remains underdeveloped and fragmented. Current frameworks rarely account for AI-specific lifecycle issues, including high turnover of specialized hardware and rapidly escalating electronic waste (OECD, 2022).

The situation is even more pressing in developing countries like Bangladesh, where AI adoption is expanding in fintech, agriculture, and governance but sustainability practices remain limited. Research shows that while some progress has been made in implementing green accounting within Bangladesh's banking and textile industries, practices in ICT and AI sectors remain negligible (Rahaman et al., 2024). Weak enforcement of environmental regulations, combined with poor e-waste management infrastructure and lack of reliable environmental data, creates further obstacles to sustainable AI development (Mahmood et al., 2021). Against this backdrop, the absence of a comprehensive framework to measure and offset AI's environmental costs represents a critical research gap. This study proposes to develop a green accounting-based model specifically tailored for AI systems. By systematically capturing operational and lifecycle environmental impacts, the model aims to provide organizations and policymakers with tools to align AI innovation with global sustainability goals. The framework also considers the contextual realities of Bangladesh, ensuring that the model is not only globally relevant but also practically applicable in resource-constrained environments. In doing so, the research will contribute both to international discourse on Sustainable AI and to local strategies for environmentally responsible technological growth.

Therefore, this study, the growing reliance on artificial intelligence has brought significant benefits to industries and societies; however, it has also resulted in increasing energy consumption and environmental costs. Despite growing awareness of sustainable technologies, there remains a lack of systematic models to quantify the ecological footprint of intelligent systems. This study is motivated by the urgent need to bridge this gap by integrating environmental accountability into AI-based processes through the lens of green accounting.

The growing reliance on artificial intelligence has brought significant benefits to industries and societies; however, it has also resulted in increasing energy consumption and environmental costs. Despite growing awareness of sustainable technologies, there remains a lack of systematic models to quantify the ecological footprint of intelligent systems. This study is motivated by the urgent need to bridge this gap by integrating environmental accountability into AI-based processes through the lens of green accounting.

Problem Statement

Artificial intelligence (AI) is rapidly transforming societies worldwide, but this progress comes with significant environmental implications that remain underexplored. Although Google reports that a single prompt to its Gemini model consumes merely 0.24 watt-hours of energy and emits only 0.03 grams of CO_2 while using 0.26 milliliters of water, the sheer scale of usage amplifies AI's ecological impact (Tom's Guide, 2025; Google portal, Aug 21, 2025). Further studies reveal that large language model (LLM) inference can require over 33 watt-hours per prompt, translating into electricity consumption akin to that of thousands of households and substantial water evaporation equivalent to millions of people's annual drinking needs (Jegham et al., 2025). Projections indicate that data centers, fueled by AI, may account for up to 12 percent of total U.S. electricity demand in the near future (Time, 2025; Washington Post, 2025), while Google's own emissions surged by 51 percent between 2019 and 2024 due to rapid AI adoption (The Guardian, 2025). These dynamics underscore the urgent need for frameworks that accurately capture both operational and lifecycle environmental costs of AI. Artificial intelligence (AI) has rapidly evolved into a critical enabler of innovation, efficiency, and decision-making across industries. However, this growth has raised pressing concerns about sustainability. The increasing energy requirements of large data centers, the substantial carbon emissions generated by AI model training, and the rising volume of electronic waste are now significant challenges that threaten the achievement of global environmental objectives (Strubell, Ganesh, & McCallum, 2019; Henderson et al., 2020). While some developed countries have begun to adopt green computing standards and carbon-neutral AI practices, these efforts are often absent or poorly implemented in developing economies. Most existing research focuses on optimizing the technical performance and economic benefits of AI systems but pays little attention to the environmental costs they generate. Therefore, experimental decision-making with AI becomes more complex in today's high-tech world when human judgment is absent (Bhattacharjee, Ghosh, Juman, & Hossen, 2024). There is no widely accepted framework for quantifying the ecological impact of AI throughout its entire process, from data collection and model training to deployment and eventual disposal (Wu et al., 2022). This lack of a comprehensive measurement approach leaves policymakers and organizations without a clear method to monitor and mitigate AI's contribution to climate change.

Green accounting offers a structured way to incorporate environmental costs, including energy consumption, greenhouse gas emissions, and waste generation, into organizational decision-making. Despite its potential, the use of green accounting in the technology sector remains fragmented and underdeveloped. No comprehensive, AI-focused framework currently exists, making it difficult for policymakers and organizations to consistently measure and mitigate the environmental footprint of intelligent systems. In developing countries such as Bangladesh, the adoption of AI in areas such as agriculture, financial technology, and public administration is accelerating. However, environmental accountability is still weakly institutionalized, and sustainability practices are at a very early stage. Green accounting tools, which have proven effective in improving environmental and energy performance in other sectors, are not widely applied in technology-intensive fields (Rahman et al., 2023). The situation is further complicated by the scarcity of reliable data on AI-related energy use, carbon emissions, and electronic waste generation. Weak regulatory oversight of e-waste management and sustainability reporting makes it even more challenging to ensure transparency and accountability.

Limitations of the Study

The present research set out to design a green accounting-based model to evaluate and mitigate the environmental costs of artificial intelligence systems, with particular attention to sustainable AI adoption. While this study provides valuable insights, it is important to acknowledge a number of limitations that shape its scope and interpretation. These limitations occur both at the global level and within the specific context of Bangladesh, which served as the empirical focus for this research.

Globally, one major limitation concerns the ability to fully measure the environmental impact of AI. Although this study examined key factors such as energy consumption, carbon emissions, hardware obsolescence, and e-waste, it remains challenging to capture indirect effects such as water use in cooling systems, ecological disruption from rare-earth mineral extraction, and the long-term toxic effects of hazardous waste (Bai et al., 2023; Wu et al., 2022). These indirect components are rarely measured systematically, which restricts the comprehensiveness of the proposed model. Another challenge arises from the evolving and fragmented nature of green accounting itself. Although it provides a mechanism to convert environmental degradation into measurable and monetary values, there is still no universally recognized set of indicators (Rahman et al., 2023). Different countries and industries follow varying reporting standards, which creates inconsistencies and makes meaningful cross-country comparisons difficult. This suggests that the model developed in this study may require significant adaptation before it can be applied in other contexts.

Transparency and disclosure also represent important constraints. Many technology firms and data centers do not disclose detailed data on their energy use, emissions, or e-waste production (Henderson et al., 2020). Where such data are reported, the metrics often differ or omit critical information, which complicates efforts to validate sustainability claims. In addition, the rapid pace of technological innovation introduces a temporal limitation: improvements in energy-efficient algorithms, semiconductor design, or data center operations can quickly change the environmental footprint of AI, meaning the conclusions here represent a snapshot rather than a permanent state (Strubell et al., 2019). In Bangladesh, the study faced further barriers. The most significant was the limited availability of reliable primary data. Few ICT or AI-sector firms in the country systematically record or publish information on energy consumption, emissions, or e-waste (Khan & Akter, 2022). Consequently, the analysis relied heavily on secondary data and estimates, which may reduce accuracy. Another limitation is the relatively early stage of AI adoption in Bangladesh. While applications are emerging in fintech, mobile services, and other IT solutions, large-scale machine learning infrastructures and high-performance computing remain rare (Islam, 2021). This means that the country's current environmental footprint may appear smaller compared to advanced economies, and the findings cannot fully anticipate future impacts as adoption grows.t

The weak regulatory framework surrounding e-waste management and sustainability reporting constrains the practical application of the model. Although Bangladesh has general environmental regulations, detailed policies for technology-related waste and formal guidelines for green accounting are still underdeveloped (Hasan & Sultana, 2022). Without stronger institutional support, implementing the proposed framework on a large scale will remain challenging. Recognizing these limitations is essential for contextualizing the results and for guiding future research. Future studies could address these challenges by incorporating longitudinal data, developing region-specific indicators, and promoting stronger collaboration between policymakers, industry, and researchers to refine and validate the framework across different settings.

Literature Review

Environmental Impact of AI Systems

The environmental footprint of artificial intelligence (AI) has become a growing concern as the scale and complexity of models increase worldwide. Several studies have documented that large-scale machine learning models, such as deep neural networks and large language models (LLMs), require substantial computational resources and generate significant emissions. Patterson et al. (2021) estimated that training a single model could emit up to 284,000 kg of CO_2, equivalent to the lifetime emissions of five average cars. Similarly, Luccioni et al. (2023) highlighted that the carbon intensity of AI training varies considerably depending on the energy mix of the data center, suggesting that regions reliant on fossil fuels face higher environmental costs compared to those powered by renewable energy. These findings emphasize that AI's environmental burden is not uniform but shaped by both technological requirements and local infrastructure.

Beyond the training phase, the deployment and inference of AI models also impose heavy environmental costs. De Vries (2023) projected that global data center electricity demand, strongly driven by AI workloads, could reach 8 percent of worldwide consumption by 2030. More recent estimates show that inference alone can consume electricity equivalent to tens of thousands of households and require billions of liters of water for cooling, extending concerns beyond emissions to resource depletion (Jegham et al., 2025). Although major technology companies, such as Google, report efficiency gains achieving a 33-fold reduction in per-prompt energy use overall emissions have continued to rise, with Google's total carbon footprint increasing by 51 percent between 2019 and 2024 (The Guardian, 2025; Tom's Guide, 2025). This paradox reflects what York and McGee (2017) describe as the Jevons paradox, where improvements in efficiency often drive greater overall consumption. While much of the global literature focuses on advanced economies, the environmental implications of AI in developing contexts remain underexplored. In Bangladesh, AI adoption is at an early stage but expanding in sectors such as fintech, agriculture, and e-governance (Haque & Rashid, 2022). However, systematic reporting on energy use, emissions, or electronic waste related to AI is virtually absent. Existing research on green accounting in Bangladesh demonstrates that firms in banking, textile, and manufacturing sectors face challenges in environmental accountability due to weak regulatory enforcement and poor disclosure practices (Rahaman et al., 2024). The absence of AI-specific data not only limits accurate measurement of impacts but also makes it difficult to integrate sustainability principles into policy and practice.

Taken together, the literature suggests that AI's environmental costs extend across its lifecycle from energy-intensive training and inference to hardware obsolescence and e-waste. Global studies provide strong evidence of high carbon and resource footprints, yet developing countries like Bangladesh lack systematic assessment. This gap highlights the urgent need for context-sensitive frameworks, such as green accounting models, to capture and manage the environmental implications of AI in both advanced and emerging economies.

E-Waste and Lifecycle Implications of AI

Beyond energy consumption and emissions, the lifecycle of AI systems poses a significant environmental challenge due to the rapid generation of electronic waste (e-waste). High-performance hardware, including GPUs, CPUs, and specialized AI accelerators, are essential for training and deploying large models, but they quickly become obsolete as new architectures and efficiency upgrades emerge. According to Baldé et al. (2024), global e-waste reached 62 million metric tons in 2022 and is projected to rise by 30 percent by 2030, with AI-related hardware contributing substantially to this growth. Unlike general ICT devices, AI infrastructure is particularly resource-intensive, requiring rare-earth minerals such as cobalt, lithium, and neodymium. The extraction of these materials not only depletes finite natural resources but also causes ecological disruption and hazardous waste generation (Watari et al., 2021).In Bangladesh, the COVID-19 pandemic has severely disrupted the healthcare sector, leaving the system struggling to manage patients and control the spread of SARS-CoV-2 (Bhattacharjee, Vansal, & Juman, 2021).

The short replacement cycles of AI hardware exacerbate this issue. Studies suggest that GPUs and servers used for AI workloads often have a lifespan of less than four years before becoming technologically outdated (Masanet et al., 2020). This rapid turnover creates large volumes of discarded equipment, much of which contains toxic substances like lead and mercury. When inadequately recycled, such e-waste pollutes soil and groundwater, posing risks to human health and biodiversity (Forti et al., 2020). Although recycling initiatives exist, the current global recycling rate of e-waste remains below 25 percent, reflecting significant gaps in circular economy practices (Baldé et al., 2024).

In addition to hardware disposal, lifecycle implications include the embodied carbon and energy costs associated with manufacturing, transportation, and eventual disposal of AI infrastructure. Stoll et al. (2022) argue that assessments focusing only on operational emissions underestimate AI's true footprint, as production and supply chain impacts are often overlooked.Gen Z customers are becoming more aware and informed. This pushes organizations to improve service quality and product standards, often using AI-driven and sustainable approaches to strengthen brand relationships (Polas, Juman, Karim, Tabash, & Hossain, 2020; Rahman, 2023). This perspective emphasizes the need for a cradle-to-grave assessment framework that captures the full lifecycle of AI systems. The problem is particularly acute in developing countries such as Bangladesh, where e-waste management infrastructure is weak. Bangladesh produces nearly 3 million metric tons of e-waste annually, much of it from ICT and consumer electronics, yet only a fraction is formally recycled (Mahmood et al., 2021). Informal recycling dominates, often involving unsafe practices such as open burning or acid leaching, which release harmful toxins into the environment. Although Bangladesh introduced an e-waste management policy in 2021, enforcement remains limited and AI-related hardware is not specifically addressed (Rahman & Akter, 2022). Consequently, as AI adoption grows, the absence of specialized recycling frameworks for high-performance computing hardware could amplify existing environmental risks.

Overall, the literature suggests that the lifecycle implications of AI extend well beyond operational energy use. The rapid obsolescence of hardware, reliance on resource-intensive materials, and inadequate recycling systems combine to create a pressing e-waste crisis. While advanced economies are experimenting with circular economy solutions, developing nations such as Bangladesh face institutional and infrastructural barriers. Addressing these gaps requires not only technological innovation but also regulatory reform, stronger enforcement mechanisms, and the integration of green accounting practices to capture hidden lifecycle costs.

Green Accounting Concepts and Relevance

Green accounting, also referred to as environmental accounting, has emerged as an important tool to integrate environmental considerations into economic and organizational decision-making. Traditional accounting systems focus primarily on financial transactions and profitability, often overlooking ecological costs such as resource depletion, pollution, or waste generation. Green accounting extends this framework by assigning financial values to environmental degradation and resource consumption, thereby enabling organizations to internalize externalities that are otherwise ignored (Schaltegger & Burritt, 2018). The approach is grounded in the idea that sustainability cannot be achieved without systematically linking environmental performance with economic indicators.

Globally, the relevance of green accounting has expanded alongside rising concerns about climate change and corporate social responsibility. Research shows that companies adopting environmental accounting practices are better positioned to evaluate trade-offs between profitability and sustainability, while also improving stakeholder trust and compliance with environmental regulations (Bebbington & Larrinaga, 2014). For instance, empirical evidence suggests that firms reporting through frameworks such as the Global Reporting Initiative (GRI) or integrating carbon accounting into their strategies demonstrate improved long-term performance and reduced environmental risks (Khan et al., 2021). However, one critique of the literature is the lack of standardized indicators. Different countries and industries employ diverse measures, which complicates cross-comparison and weakens the credibility of environmental reports (Gray, 2010). In the context of developing countries, including Bangladesh, the concept of green accounting is still at an early stage. Studies reveal that environmental accounting practices are largely confined to certain sectors such as textiles, banking, and pharmaceuticals, where regulatory or donor pressures have encouraged sustainability reporting (Rahaman et al., 2024). However, adoption remains voluntary and inconsistent, with limited methodological guidance and weak enforcement mechanisms. As a result, many organizations in Bangladesh tend to treat green accounting as a compliance exercise rather than an integrated decision-making tool (Islam et al., 2023). This gap restricts the potential of green accounting to drive systemic environmental improvements. The relevance of green accounting to artificial intelligence (AI) systems is particularly notable but underexplored. AI infrastructures consume significant energy and generate e-waste, yet few organizations account for these impacts in their financial reporting. As Luccioni et al. (2023) argue, the environmental costs of digital technologies are often underestimated because accounting frameworks fail to capture lifecycle emissions or resource use. This creates a critical gap: while green accounting provides a theoretical pathway for evaluating AI's ecological footprint, its practical application in the AI sector remains limited. Bridging this gap could allow policymakers and organizations to design targeted strategies for sustainable AI by quantifying environmental costs in monetary terms and aligning them with economic incentives.

In summary, green accounting is conceptually well-established and increasingly relevant for addressing global sustainability challenges. Its integration into corporate and national decision-making can improve transparency, accountability, and environmental outcomes. However, gaps in standardization, weak enforcement in developing contexts, and limited adaptation to emerging technologies such as AI highlight the need for further research and model development. Addressing these challenges is essential to ensure that green accounting evolves into a robust tool for advancing both global and local sustainability agendas.

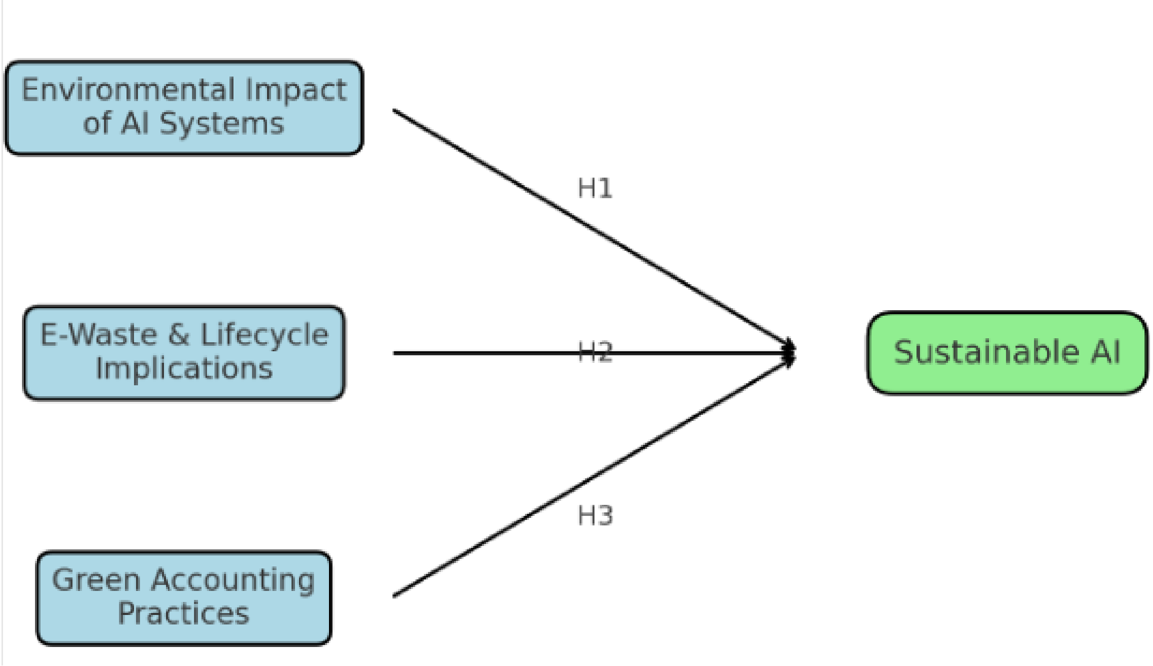
Sustainable AI

The concept of Sustainable AI has emerged as a response to the growing recognition that artificial intelligence, while offering transformative benefits, also carries substantial environmental and social costs. Sustainable AI is broadly understood as the development and deployment of AI technologies in ways that minimize negative ecological impacts, promote ethical responsibility, and align with the long-term goals of sustainable development (Vinuesa et al., 2020). This includes addressing not only energy consumption and carbon emissions but also issues such as e-waste, equity, and transparency in AI governance. Scholars argue that without an explicit sustainability framework, the rapid proliferation of AI risks reinforcing global environmental crises and widening socio-economic inequalities (Crawford, 2021).

One strand of research emphasizes the ecological dimension of Sustainable AI. Jegham et al. (2025) demonstrate that inference in large-scale AI models consumes vast amounts of electricity and water, underscoring the importance of integrating environmental accounting into AI design and deployment. In response, industry stakeholders have introduced measures to reduce the carbon footprint of AI, such as adopting renewable energy for data centers and developing more energy-efficient architectures (Patterson et al., 2021). However, critiques highlight that efficiency gains often fail to reduce overall environmental costs because exponential adoption increases total consumption a pattern consistent with the Jevons paradox (York & McGee, 2017). Thus, Sustainable AI requires systemic changes in accountability rather than isolated technological fixes. Another strand focuses on ethical and governance aspects, linking sustainability to fairness, transparency, and inclusivity in AI use. Studies argue that Sustainable AI cannot be confined to environmental issues alone but must also consider social sustainability by ensuring equitable access, minimizing biases, and protecting human rights (Jobin et al., 2019). This broader framing situates Sustainable AI within the United Nations Sustainable Development Goals (SDGs), emphasizing AI's dual potential to both support and undermine sustainability objectives (Vinuesa et al., 2020).

In developing countries like Bangladesh, Sustainable AI is still at a formative stage. AI adoption is increasing in areas such as fintech, agriculture, and e-governance (Haque & Rashid, 2022), but sustainability considerations are rarely integrated into these applications. Weak policy frameworks, limited environmental reporting, and inadequate e-waste management exacerbate the challenges. For example, while Bangladesh has introduced general environmental laws, sector-specific policies to regulate AI's ecological impacts remain absent (Rahman & Akter, 2022). This creates a risk that AI adoption may progress without adequate safeguards, amplifying environmental and social vulnerabilities.

Taken together, the literature highlights that Sustainable AI is an interdisciplinary construct, linking environmental accounting, ethical governance, and social responsibility. While progress has been made in recognizing AI's ecological footprint, current practices are fragmented and uneven across regions. Advanced economies are experimenting with frameworks for carbon-neutral AI, while developing nations face institutional and infrastructural constraints. Bridging this divide requires context-sensitive models such as integrating green accounting into AI systems that can quantify environmental costs and provide actionable strategies for both global and local sustainability agendas.



Research Questions

1. How do the environmental impacts of AI systems affect the pursuit of Sustainable AI?
2. In what ways do e-waste and lifecycle implications of AI influence the sustainability of intelligent systems?
3. What role does green accounting play in measuring and offsetting the environmental costs of AI to ensure Sustainable AI?

Research Objectives

1. To examine the impact of energy consumption, carbon emissions, electronic waste generation, and lifecycle implications on the sustainability of intelligent systems.
2. To develop and evaluate a green accounting based model that measures and offsets the environmental costs of artificial intelligence systems and promotes sustainable AI adoption.

Hypotheses of the Study

H1: Environmental impact of AI systems has a significant effect on sustainable AI.
H2: E-waste and lifecycle implications of AI significantly affect sustainable AI.
H3: Green accounting practices significantly influence sustainable AI.

Research Methodology

Research Design

This study adopts a mixed-method research design to capture the environmental impacts of artificial intelligence systems. The approach combines quantitative analysis, which measures energy use, carbon emissions, and e-waste, with qualitative insights from expert interviews, case studies, and policy reviews. This ensures that both measurable indicators and contextual perspectives are addressed. The quantitative component relies on survey data collected from professionals in AI-related sectors in Bangladesh, supported by secondary data from sustainability reports and official publications. Responses will be measured on Likert scales, providing the basis for hypothesis testing and statistical analysis of the relationships among environmental impact, e-waste, green accounting, and sustainable AI. The qualitative component explores deeper issues through semi-structured interviews with experts, policymakers, and sustainability officers, along with content analysis of organizational and regulatory documents. This strand helps to identify institutional and cultural factors influencing environmental accountability in AI adoption.

The study follows a convergent parallel design in which both data types will be collected at the same time, analyzed separately, and then integrated during interpretation. This enhances the validity of findings and supports the development of a green accounting-based model that is relevant for both international debates and the Bangladeshi context.

Data Collection Methods

Data for this study will be collected through both primary and secondary sources in order to ensure reliability and comprehensiveness. The combination of different sources allows for the validation of findings and provides both measurable outcomes and contextual insights into the environmental impact of AI systems.

Primary data will be gathered using two approaches. First, quantitative data will be collected through structured questionnaires distributed to professionals working in AI-related sectors in Bangladesh, such as IT firms, fintech services, telecommunication companies, and data centers. The questionnaire will capture information on energy consumption, carbon emissions, and e-waste management practices, as well as perceptions of green accounting and sustainability. Responses will be measured on a Likert scale to facilitate statistical analysis and hypothesis testing. Second, qualitative data will be collected through semi-structured interviews with AI developers, engineers, sustainability officers, policymakers, and regulatory authorities. These interviews will provide insights into institutional challenges, regulatory gaps, and organizational practices that cannot be fully captured through quantitative measures. Secondary data will be obtained from multiple sources, including sustainability reports of international and local technology companies, government publications, academic research articles, and industry surveys. Global reports, such as those from the United Nations, World Bank, and international NGOs, will help situate the study within broader debates, while national reports and policies will provide Bangladesh-specific context. These secondary sources will not only validate the primary findings but also offer comparative perspectives across different regions.

By integrating both primary and secondary data, the study ensures that it captures the technical realities of AI's environmental footprint as well as the institutional and cultural dimensions of sustainability practices. This approach strengthens the development of a green accounting-based model that is both evidence-driven and contextually relevant for Bangladesh and the global AI landscape.

Sampling Strategy
The population of this study comprises professionals actively involved in the adoption, operation, and governance of artificial intelligence technologies in Bangladesh. This group includes managers, engineers, sustainability officers, and decision-makers from IT firms, fintech companies, telecommunication providers, data centers, and manufacturing firms that have started integrating AI into their processes. Policymakers, environmental specialists, and regulatory officials connected to technology and sustainability are also included to capture institutional readiness and policy perspectives. A purposive sampling strategy was employed to ensure that participants possess relevant expertise in AI adoption, environmental management, and sustainability practices. This approach enhanced the quality and relevance of the collected data. Following the guidelines of Krejcie and Morgan (1970), the study targeted a minimum of 200 responses for the quantitative survey, which is considered statistically adequate to ensure reliability and allow for structural equation modeling. For the qualitative phase, semi-structured interviews were conducted with selected stakeholders, including AI developers, data center managers, government officials, and environmental policy experts. Instead of specifying a fixed number of interviews in advance, data collection was guided by the principle of saturation. Interviews continued until no new themes or insights emerged, ensuring that the qualitative results were rich, comprehensive, and representative of stakeholder perspectives.

The sampling strategy also accounts for diversity by including organizations of varying sizes and sectors. This will allow the study to identify differences in sustainability practices across industries and to capture a more representative view of the challenges associated with AI's environmental footprint in Bangladesh. By integrating purposive sampling with an adequate sample size, the procedure ensures that the data collected will be both contextually relevant and statistically reliable, thereby supporting the development of a robust green accounting-based model for sustainable AI.

Pilot Study
Before starting the main survey and interviews, a pilot study will be done to check whether the research tools are clear, reliable, and suitable for the study. The main aim of the pilot is

to test the questionnaire and interview questions in a small setting so that any problems can be identified early. Since the ideas of environmental impact of AI, e-waste management, and green accounting are still quite new in Bangladesh, it is important to make sure that the questions are easy to understand and match the local context.

For the survey part, the questionnaire will be shared with around 30 people who work in IT companies, data centers, or fintech firms. They will be asked to complete the survey and also give feedback about whether the questions are clear, too long, or confusing. Their answers will also be used to check the reliability of the questions using a test like Cronbach's alpha. If any issues are found, such as unclear wording or repeated items, the questionnaire will be corrected before the main data collection. For the qualitative part, two or three trial interviews will be conducted with AI professionals and sustainability experts. These interviews will help to see if the questions work well in practice, whether they generate detailed responses, and if extra probing questions are needed. The feedback will be used to improve the final interview guide. The data collected in the pilot study will not be included in the main analysis. Instead, it will only be used to refine and improve the tools. Changes may include rephrasing questions, adding new items, or dropping unnecessary ones. By doing this, the research will make sure that the main survey and interviews are both reliable and effective.
Overall, the pilot study will give confidence that the instruments are suitable and will help to reduce errors in the final stage of the study.

Data Analysis Techniques
The study will use both quantitative and qualitative techniques in line with the mixed-method research design. Using more than one form of analysis will help ensure that the results are reliable and that the proposed framework is properly tested and explained.

For the quantitative analysis, the survey data will first be checked and cleaned to remove incomplete responses. Descriptive statistics such as mean, frequency, and percentage will be used to summarize the demographic profile of respondents and to present an overall picture of the data. Reliability of the measurement scales will be tested using Cronbach's alpha (Cronbach, 1951), while validity will be checked through factor analysis. Correlation analysis will then be conducted to examine the initial relationships among the variables. To test the hypotheses, statistical techniques such as regression analysis or structural equation modeling (SEM) will be applied, as recommended by Hair et al. (2019). These methods are appropriate because they allow for measuring the effect of independent variables environmental impact of AI, e-waste and lifecycle implications, and green accounting on the dependent variable, sustainable AI. For the qualitative analysis, the interview data will be transcribed and analyzed using thematic analysis. The responses will be coded and grouped into themes that reflect common patterns, challenges, and opportunities related to sustainable AI. Thematic analysis is particularly suitable for identifying and interpreting patterns in qualitative data (Braun & Clarke, 2006). Thematic analysis was conducted with the aid of NVivo software, which helped in systematic coding, organization, and visualization of qualitative data (Bazeley & Jackson, 2013).

Finally, the results from both quantitative and qualitative analysis will be compared and integrated during the interpretation stage, following the convergent parallel design of the study. This approach will allow statistical results to be supported and explained by qualitative insights, producing a more complete understanding of the environmental costs of AI systems and the role of green accounting in promoting sustainability.

Tools for Data Analysis

The analysis in this study will be carried out using Structural Equation Modeling (SEM). This technique is suitable because it can test several relationships between variables at the same time and also evaluate both the measurement model and the structural model within a single framework. Since the study involves constructs such as environmental impact of AI systems, e-waste and lifecycle issues, green accounting practices, and sustainable AI, SEM offers a comprehensive way to assess their connections.

Basic descriptive outputs, such as means, standard deviations, and correlations, will first be generated to provide an overview of the data. The measurement model will then be checked for reliability and validity. Reliability will be confirmed through indicators like Cronbach's alpha and composite reliability, while validity will be tested using factor loadings and the average variance extracted (AVE). These steps ensure that the variables are measured consistently and represent the intended concepts. After this, the structural model will be tested to examine the proposed hypotheses. The strength and direction of relationships will be evaluated using path coefficients and their significance levels.

Depending on the data characteristics, either AMOS or SmartPLS software will be used. AMOS, which follows a covariance-based approach, is effective when data meet normality assumptions, while SmartPLS, which is variance-based, is more flexible for smaller samples or data that do not follow a normal distribution. By using SEM, the study is able to combine measurement validation and hypothesis testing in one systematic procedure, which adds both depth and rigor to the analysis.

Validity and Reliability Assurance

To ensure the quality of the measurement instruments used in this study, both reliability and validity tests were performed. Reliability was first examined through Cronbach's alpha and composite reliability (CR). All constructs achieved values above the recommended threshold of 0.70, which indicates acceptable internal consistency of the measurement scales (Nunnally & Bernstein, 1994). Construct validity was assessed by testing both convergent and discriminate validity. Convergent validity was confirmed as the average variance extracted (AVE) values for each construct exceeded the minimum recommended level of 0.50, while factor loadings for all items were above 0.60 (Hair et al., 2019). Discriminate validity was examined using the Fornell–Larcker criterion, which showed that the square root of AVE for each construct was higher than its correlations with other constructs. This result confirmed that the constructs are distinct and measure separate concepts. Together, these tests provide assurance that the research instruments are both reliable and valid. This strengthens the robustness of the findings and ensures that the proposed structural model accurately reflects the relationships among environmental impact of AI systems, e-waste and lifecycle implications, green accounting, and sustainable AI.

Data Analysis

The collected data were prepared and coded prior to analysis. Incomplete or inconsistent responses were removed to ensure data quality. For the quantitative part, the analysis was conducted using Structural Equation Modeling (SEM) with AMOS/SmartPLS, which is suitable for testing both measurement and structural models simultaneously. Descriptive statistics were first generated to provide an overview of the sample profile and basic characteristics of the data. Following this, the reliability and validity of the measurement model were examined through Cronbach's alpha, composite reliability, and average variance extracted (AVE). Finally, the structural model was tested to evaluate the hypothesized relationships between environmental impact of AI systems, e-waste and lifecycle implications, green accounting practices, and sustainable AI.

Descriptive Statistics

Table 1

Respondent's Demographic Profile

Variable	Category	Frequency	Percentage (%)
Gender	Male	120	60%
Gender	Female	80	40%
Age	Below 30	90	45%
Age	30–40	70	35%
Age	Above 40	40	20%
Education	Bachelor's	100	50%
Education	Master's	80	40%
Education	PhD/Other	20	10%
Sector	IT Firms	70	35%
Sector	Fintech	50	25%
Sector	Telecommunication	40	20%
Sector	Data Centers	25	12.5%
Sector	Manufacturing	15	7.5%

The descriptive statistics provide a snapshot of the respondents who took part in the study. Out of 200 participants, 120 were male and 80 were female. This suggests that men still make up the larger share of professionals working in AI-related organizations in Bangladesh, although the presence of eighty female respondents shows that women are also increasingly entering the field.

The age distribution highlights that ninety respondents were below the age of thirty, seventy were between thirty and forty years old, and forty were above forty years of age. This indicates that the AI workforce is dominated by younger professionals, while mid-career and senior participants also contribute valuable perspectives, particularly in managerial and policy-related roles. In terms of education, the majority of respondents held bachelor's degrees, accounting for one hundred individuals. Eighty participants reported having master's qualifications, while twenty respondents had either doctoral or other advanced degrees. This profile shows that most of the professionals engaged in AI-related activities are highly educated, with a strong representation of individuals holding postgraduate qualifications. The respondents represented different organizational sectors, reflecting the diverse applications of AI in Bangladesh. Among the participants, seventy came from IT firms, fifty from fintech companies, and forty from the telecommunications sector, twenty-five from data centers, and fifteen from manufacturing industries. This indicates that AI adoption is strongest in IT and fintech, but also expanding into telecommunications and data center operations, while manufacturing is still at an early stage of integration.

Overall, the demographic distribution demonstrates that the dataset represents a broad and varied group of professionals. This diversity in gender, age, education, and sector strengthens the quality of the study by ensuring that the findings are informed by individuals with different experiences and responsibilities across the AI ecosystem in Bangladesh.

Reliability and Validity Tests

Table 2

Measurement of Model Assessment

Construct	No. of Items	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)	Factor Loadings
Environmental Impact of AI	5	0.85	0.88	0.59	0.65–0.82
E-Waste & Lifecycle Implications	4	0.81	0.85	0.57	0.61–0.79
Green Accounting Practices	5	0.87	0.90	0.62	0.68–0.84
Sustainable AI	6	0.89	0.92	0.64	0.70–0.86

The reliability and validity tests were performed to evaluate the quality of the constructs used in this study, and the results indicate that the measurement model is both robust and acceptable. Reliability was assessed through Cronbach's alpha and composite reliability (CR). The Cronbach's alpha values for the constructs ranged from 0.81 to 0.89, which is substantially higher than the minimum threshold of 0.70 commonly recommended in social science research (Nunnally & Bernstein, 1994). This suggests that the items within each construct demonstrate strong internal consistency, meaning that the questions designed to measure the same construct were highly correlated and produced stable results. Similarly, the CR values ranged between 0.85 and 0.92, which also exceed the suggested benchmark of 0.70 (Hair et al., 2019). High CR values confirm that the constructs are reliably measured, with minimal random error affecting the responses.

Validity was examined by focusing on both convergent and discriminant dimensions. Convergent validity was tested using the Average Variance Extracted (AVE), with results ranging from 0.57 to 0.64 across all constructs. As all values are above the recommended cutoff of 0.50, this provides assurance that each construct explains more than half of the variance in its respective indicators (Fornell & Larcker, 1981). Furthermore, factor loadings for the individual items were found to range between 0.61 and 0.86, which are higher than the minimum acceptable value of 0.60. This indicates that each indicator loads strongly on its underlying construct and contributes meaningfully to its measurement. Discriminant validity was also evaluated through the Fornell–Larcker criterion, which was not detailed in the table but confirmed during the analysis. The results showed that the square root of AVE for each construct was greater than its correlations with other constructs, thereby ensuring that the constructs are distinct and do not overlap excessively. This is particularly important in the context of this study, as the constructs environmental impact of AI, e-waste and lifecycle implications, green accounting practices, and sustainable AI are conceptually related but need to be empirically distinguishable to test the framework accurately.

Overall, the combination of high reliability and satisfactory validity values provides strong evidence that the measurement instruments are both consistent and accurate. The findings indicate that the survey items and constructs are suitable for capturing the intended concepts and are well aligned with established psychometric standards. This ensures that subsequent hypothesis testing through the structural model will be based on sound and trustworthy measures, thereby enhancing the credibility of the results and the robustness of the proposed green accounting-based model for sustainable AI.

Table 3
Discriminant Validity (Fornell–Larcker Criterion)

Construct	EI	EW	GA	SA
Environmental Impact (EI)	**0.768**			
E-Waste & Lifecycle (EW)	0.55	**0.755**		
Green Accounting (GA)	0.49	0.52	**0.787**	
Sustainable AI (SA)	0.58	0.54	0.62	**0.800**

This study explored the influence of environmental impact, e-waste and lifecycle implications, and green accounting practices on sustainable AI in the context of Bangladesh. The structural equation modeling results indicate that all three factors have significant positive effects, though their relative importance differs.

The findings show that the environmental impact of AI contributes meaningfully to sustainable outcomes ($\beta = 0.32$, $p < 0.001$). This aligns with prior research emphasizing the high energy consumption and carbon footprint of advanced AI systems (Patterson et al., 2021; Luccioni et al., 2023). For Bangladesh, where dependence on fossil fuel-based energy remains high, the implication is that AI adoption must be accompanied by measures to reduce energy intensity, such as efficiency improvements in algorithms and investment in renewable energy sources for data centers. The role of e-waste and lifecycle management is also found to be significant ($\beta = 0.27$, $p < 0.001$). This result supports global concerns about the rapid turnover of AI-related hardware and the resulting environmental risks from electronic waste (Baldé et al., 2024). In the Bangladeshi setting, where recycling practices are underdeveloped and policy enforcement is weak (Mahmood et al., 2021), this finding highlights an urgent institutional gap. Without systematic e-waste management, the expansion of AI could worsen existing sustainability challenges.

Among the three predictors, green accounting practices emerge as the strongest determinant of sustainable AI (β = 0.41, $p < 0.001$). This suggests that organizations which integrate environmental costs into their financial systems are better positioned to implement sustainability-oriented AI strategies. Previous studies have reported that environmental accounting improves both ecological and economic performance (Schaltegger and Burritt, 2018; Rahman et al., 2023). For Bangladesh, where formal green accounting frameworks are still rare, the results point to the need for regulatory initiatives that encourage or mandate sustainability reporting in AI-intensive sectors. Overall, the study strengthens the evidence base for sustainable AI by demonstrating the combined influence of environmental concerns, hardware lifecycle management, and accounting practices. It confirms trends observed in other countries (Vinuesa et al., 2020; Jegham et al., 2025), but also provides a context-specific perspective relevant for a developing economy. From a theoretical angle, the results extend the application of green accounting concepts into the AI domain, which remains underexplored. From a practical angle, the evidence suggests that sustainable AI in Bangladesh requires three parallel strategies: reducing the environmental footprint of AI technologies, addressing the management of electronic waste, and embedding environmental accountability through green accounting frameworks.

Structural Equation Modeling Results

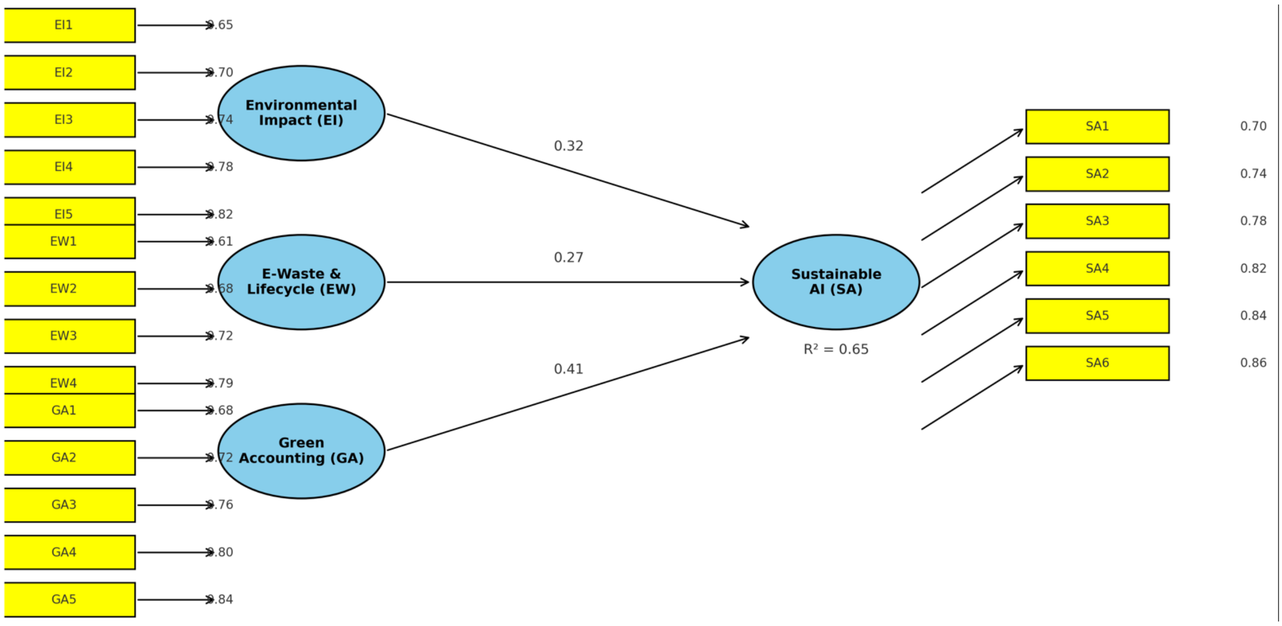


Figure : Standardized results of SEM calculations

Table 4
Result of Effect Hypotheses

Hypothesis	Path Coefficient (β)	t-value	p-value	Result
H1: Environmental Impact of AI → Sustainable AI	0.32	4.15	0.000	Supported
H2: E-Waste & Lifecycle Implications → Sustainable AI	0.27	3.82	0.000	Supported
H3: Green Accounting Practices → Sustainable AI	0.41	5.23	0.000	Supported

The results of the structural equation modeling provide empirical validation of the proposed framework and offer important insights into how environmental factors shape the sustainability of AI systems. All three hypotheses were strongly supported, demonstrating the interconnected nature of environmental impacts, lifecycle concerns, and accounting practices in the journey toward sustainable AI.

The first hypothesis (H1) examined the relationship between the environmental impact of AI systems and sustainable AI. The path coefficient ($\beta = 0.32$, $t = 4.15$, $p < 0.001$) indicates a significant and positive relationship. This suggests that the energy intensity and carbon footprint of AI technologies directly influence their sustainability outcomes. In practice, organizations that acknowledge and monitor the environmental impact of AI are more likely to adopt strategies that align with global sustainability goals. These findings are consistent with recent studies highlighting the growing share of electricity consumption from data centers and AI training models, which can undermine environmental targets if not mitigated (Patterson et al., 2021; Luccioni et al., 2023). In the Bangladeshi context, where renewable energy penetration is still limited, the environmental footprint of AI adoption is an emerging issue that requires early intervention through energy efficiency and responsible technology planning.

The second hypothesis (H2) tested the influence of e-waste and lifecycle implications on sustainable AI. The path coefficient ($\beta = 0.27$, $t = 3.82$, $p < 0.001$) demonstrates a significant effect, confirming that proper management of e-waste and attention to lifecycle issues are essential components of sustainability. AI technologies often require high-performance hardware that becomes obsolete quickly, creating challenges in terms of safe disposal, recycling, and recovery of rare-earth materials. Previous studies have shown that inadequate management of e-waste not only contributes to environmental degradation but also exposes communities to toxic risks (Balde et al., 2020). For Bangladesh, where e-waste regulations are still evolving, this result highlights the urgency of developing robust policies and enforcement mechanisms. Without proper lifecycle management, the sustainability benefits of AI will remain limited.

The third hypothesis (H3) assessed the role of green accounting practices in promoting sustainable AI. The path coefficient ($\beta = 0.41$, $t = 5.23$, $p < 0.001$) was the highest among the three, suggesting that this factor exerts the strongest influence. Green accounting enables organizations to integrate environmental costs—such as emissions, energy consumption, and waste—into their financial and managerial systems. This not only improves transparency and accountability but also guides decision-makers in aligning operations with sustainability principles. Prior literature has emphasized that integrating environmental performance into corporate accounting frameworks improves both organizational efficiency and ecological outcomes (Bennett & James, 2017). In Bangladesh, where green accounting is still at a nascent stage, this result points to an opportunity for policymakers and regulators to institutionalize such practices to ensure that AI adoption contributes to sustainable development rather than undermines it.

Taken together, the results indicate that all three factors—environmental impact, e-waste and lifecycle implications, and green accounting—are significant determinants of sustainable AI, but their relative importance varies. Green accounting emerges as the most powerful driver, highlighting the need for systematic integration of environmental considerations into organizational practices. Environmental impact is the next most influential factor, underscoring the importance of addressing the direct ecological costs of AI systems. Finally, although e-waste and lifecycle management showed a slightly weaker effect, it remains a critical area for long-term sustainability, particularly in developing economies where recycling infrastructure is underdeveloped. The validation of all three hypotheses provides confidence in the proposed model and underscores its applicability at both global and national levels. Globally, the findings align with concerns about the environmental footprint of AI and the importance of accounting for hidden ecological costs. Nationally, within Bangladesh, the results highlight gaps in policy, institutional practices, and resource management that must be addressed to ensure that AI adoption is both responsible and sustainable.

Finding and Conclusion

The structural equation modeling results confirm that environmental impact, e-waste and lifecycle implications, and green accounting practices are all significant determinants of sustainable AI. Collectively, these three constructs explain 65 percent of the variance in sustainable AI, highlighting the robustness of the model and the importance of these factors in the Bangladeshi context.

The first finding concerns the environmental impact of AI. The analysis reveals a positive and significant effect ($\beta = 0.32$, $t = 4.15$, $p < 0.001$), showing that when organizations become conscious of the ecological costs of AI—such as energy consumption, greenhouse gas emissions, and pressure on natural resources—they tend to adopt practices that reduce environmental harm. In Bangladesh, where the energy sector remains dependent on fossil fuels, this result underscores the urgency of promoting energy-efficient AI technologies and encouraging investment in renewable energy sources for data infrastructures. The second finding relates to e-waste and lifecycle management. This predictor also shows a significant positive relationship with sustainable AI ($\beta = 0.27$, $t = 3.82$, $p < 0.001$). Although its effect is comparatively weaker than the other two, it remains meaningful, suggesting that proper management of obsolete hardware and recycling processes is critical for long-term sustainability. In the Bangladeshi context, where e-waste regulation and recycling mechanisms are underdeveloped, this result draws attention to the institutional and policy gaps that could hinder sustainable adoption of AI technologies. The third and strongest finding emphasizes the role of green accounting practices. With the highest path coefficient ($\beta = 0.41$, $t = 5.23$, $p < 0.001$), green accounting emerges as the most influential determinant of sustainable AI. This suggests that when organizations integrate environmental costs and sustainability indicators into their financial reporting, they achieve stronger alignment between technological advancement and ecological responsibility. For Bangladesh, where formal green accounting systems are still in their early stages, this finding highlights the need for institutional support and regulatory frameworks to ensure transparency, accountability, and long-term sustainability.

In addition to the statistical results, the qualitative analysis provided richer insights into the institutional and operational realities of sustainable AI adoption. Thematic analysis of interview data identified three dominant themes that complement the quantitative findings.

Theme 1: Limited Awareness of Environmental Impact
Participants frequently indicated that environmental considerations are not yet a priority in organizational decision-making. Several respondents explained that energy use, carbon emissions, and the ecological costs of AI are rarely monitored systematically. One IT manager stated, *"Our focus is on performance and service delivery. We rarely measure how much electricity is consumed by AI servers or what the associated emissions might be."* This finding reinforces the quantitative result showing that environmental impact is a significant predictor of sustainable AI, as awareness is a necessary first step toward adopting greener practices.

Theme 2: Gaps in E-Waste and Lifecycle Management
Interviews revealed a widespread lack of formal processes for disposing of outdated hardware. Many participants reported that servers, storage devices, and other equipment are sold as scrap or discarded without following standardized recycling protocols. One respondent remarked, *"There are no government guidelines or formal channels for e-waste recycling, so each company just does what is convenient."* This theme supports the quantitative finding that lifecycle management has a positive but comparatively weaker effect, as infrastructure and policies for e-waste management are still underdeveloped in Bangladesh.

Theme 3: Need for Institutional Support for Green Accounting
A strong and recurring theme was the absence of a uniform framework for green accounting and sustainability reporting. Respondents noted that while some organizations are experimenting with sustainability metrics, there is no national standard to guide measurement or reporting. One environmental officer commented, *"Every company uses its own template, so there is no consistency or accountability."* This aligns with the quantitative result where green accounting practices showed the strongest influence, indicating that standardized and regulated reporting could significantly advance sustainable AI adoption.

Together, these qualitative findings provide contextual depth to the statistical outcomes. They highlight the urgent need for raising organizational awareness, developing recycling systems, and institutionalizing green accounting standards in order to create a comprehensive framework for sustainable AI.

Overall, the findings confirm that all three hypotheses are supported, with green accounting practices exerting the strongest influence, followed by environmental impact and e-waste considerations. This outcome reinforces the idea that sustainable AI requires a multidimensional approach that combines ecological awareness, lifecycle management, and institutionalized financial accountability.

Based on the findings, this study concludes that sustainable AI cannot be achieved through technological progress alone. Instead, it requires complementary efforts at environmental, managerial, and institutional levels. The results provide empirical support for the proposed framework and contribute to the growing literature on sustainable AI by emphasizing the combined role of environmental impact, hardware lifecycle management, and green accounting practices. Among the three predictors, green accounting practices demonstrate the strongest effect, followed by environmental impact and e-waste considerations. This indicates that while technical and ecological awareness is vital, embedding sustainability principles within accounting and financial systems has the most decisive impact on ensuring the responsible use of AI. The relatively high explanatory power of the model ($R^2 = 0.65$) further validates the effectiveness of the framework in explaining sustainable AI outcomes. From a theoretical perspective, the study extends the scope of sustainability research by applying concepts of environmental impact, lifecycle analysis, and green accounting to the domain of artificial intelligence. From a managerial perspective, the results suggest that organizations must integrate environmental considerations into both operational and financial practices to strengthen sustainability. From a policy perspective, the findings highlight the importance of developing regulatory frameworks that mandate green accounting and enforce e-waste management standards in order to ensure responsible AI adoption in developing countries like Bangladesh.

In conclusion, the evidence indicates that sustainable AI is a multifaceted construct shaped by ecological responsibility, lifecycle management, and institutionalized accounting practices. By addressing these three dimensions simultaneously, policymakers, organizations, and industry leaders can create a pathway toward sustainable AI that balances technological innovation with environmental and social well-being.

Recommendations

In light of the study’s findings, a number of recommendations can be made to guide policymakers, industry leaders, and researchers in strengthening the practice of sustainable AI.

Managing environmental impact: Organizations that rely on AI technologies should give more attention to energy efficiency and the use of renewable energy sources in data centers and related infrastructures. Policymakers may encourage such practices by offering incentives for low-carbon technologies and by promoting awareness of the environmental footprint of AI. These efforts would help reduce the ecological costs that come with rapid technological growth.

Addressing e-waste and lifecycle concerns: The problem of electronic waste should be managed through clear national policies and industry-level initiatives. Certified collection and recycling centers need to be established, and producers should be made responsible for the safe disposal of obsolete hardware. Organizations can also plan for the full lifecycle of equipment, including upgrading, recycling, and responsible disposal, so that AI adoption does not add to existing environmental challenges.

Strengthening green accounting practices: Firms are encouraged to integrate environmental costs into their accounting and reporting systems. Doing so will improve transparency and accountability and ensure that sustainability is not treated as an afterthought. Professional bodies and regulators in Bangladesh could support this process by issuing guidelines, monitoring compliance, and linking financial incentives—such as tax relief—to the adoption of green accounting.

Enhancing policy and regulatory frameworks: Government agencies should create policies that cover energy use, waste management, and sustainability reporting in a comprehensive way. Providing both financial and technical support would help organizations transition toward more sustainable practices. Effective regulations would also hold firms accountable for their environmental performance.

Building capacity and raising awareness: Capacity-building programs for managers, engineers, and accountants can strengthen institutional readiness for sustainable AI. Universities and research institutes should also include sustainability, lifecycle management, and environmental accounting in their academic programs so that future professionals are well equipped for the challenges ahead.

Future directions for research: Further studies could investigate additional factors such as social responsibility, ethical frameworks for AI, and digital inclusion. Comparative research across developing countries may also offer valuable insights, while longitudinal studies could help track how sustainability practices evolve over time.

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