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STRATEGIES AND BARRIERS FOR GREEN AI ADOPTION: A SURVEY OF ENERGY-EFFICIENT DEEP LEARNING PRACTICES IN PAKISTAN'S TECH ECOSYSTEM

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Abstract
The emergence of artificial intelligence (AI) has become an issue of concern because of its effect on the environment, especially with the consumption of a lot of energy in deep learning models. This paper explores the strategies and obstacles that affect the use of Green AI practices by AI professionals in the technology ecosystem in Pakistan. The survey was performed using a quantitative method in the survey of 100 software house and start up and research institutions professionals. The analysis of data was done through PLS-SEM that would facilitate the research of the relations between Sustainability Awareness, Technological Readiness, Financial Constraints, Organizational Sustainability Strategies, and Green AI Adoption. The results show that Sustainability Awareness, Technological Readiness, and Organizational Sustainability Strategies have a positive impact on adoption, whereas Financial Constraints have negative implications on implementation. The paper will offer useful suggestions to organizations, policymakers, and stakeholders to improve energy-efficient AI activities and also add to the theoretical literature on sustainable AI implementation in developing economies.

INTRODUCTION
Artificial Intelligence (AI) is a revolutionary technology that is defining current digital economy and industrial innovation. Nonetheless, the swift AI systems growth, especially deep learning models, has cast grave doubts about its environmental effect as the systems have high computational capabilities and energy use in training and deploying the models. The increased energy consumption, carbon emissions, and strain on energy infrastructure have been driven by the rising demand of computational resources in the large-scale AI models. As such, the Green AI concept has appeared as a solution that focuses on power-efficient algorithms, eco-friendly computing, and AI in a green way (Mathew, 2025; Ahmad et al., 2025).

Green AI aims at maximizing the computational efficiency without compromising the model performance in order to lower the environmental impact of AI technologies. The methods of compressing models, training models with energy awareness, hardware optimization, and efficient data processing are also actively studied to achieve the sustainability of AI systems. Researchers underline that energy-efficient practices could play an important role in the sustainable technological advancement and environmental protection, when included in the AI development (Zafar, 2025; Yarally et al., 2023). With the spread of AI in industries, new sustainability factors have become a crucial part of responsible engineering when considering AI.

Green AI has an opportunity and challenge in developing countries like Pakistan. The emerging digital economy of the country such as Software houses, startups and AI research laboratories are increasingly looking at AI driven solutions to economic growth and advancement in technology. Meanwhile, a shortage of technological resources, the absence of knowledge on sustainable AI usage, and budget restrictions can become obstacles to the implementation of energy-efficient AI (Usman et al., 2025; Ali et al., 2024). It is then essential to understand these impediments and find the optimal approach to the adoption of Green AI in the Pakistani tech ecosystem to foster sustainable technological development.

Moreover, sustainable computing as a subset of AI development can be integrated into more extended environmental targets by conserving energy, reducing the effects of climate change, and transformation of a digital world in a sustainable manner. According to previous research, the implementation of green technologies may also be determined by the awareness of organizations, technological preparedness, the backing of policies, and eco-awareness (Zhao et al., 2025; Park, 2025). Nevertheless, the empirical studies regarding the strategies and obstacles to the adoption of Green AI in the technology industry in Pakistan are scarce. Thus, the paper will examine the obstacles and implementation strategies of energy-efficient deep learning practice in the transforming AI and technology environment in Pakistan.

Aim of the Study

The main objective of the study is to look into the strategies and barriers affecting the implementation of Green AI practices especially energy-efficient deep learning methods, in the Pakistani technology ecosystem.

Research Objectives

1. To test the awareness of AI practitioners in Pakistan about the Green AI and energy-saving practice of deep learning.
2. To determine the major technological, organizational, and financial obstacles to the adoption of Green AI.
3. To discuss strategies that companies use to adopt energy efficient AI solutions.
4. To examine the connection between sustainability awareness as well as technological preparedness and adoption of Green AI practices.

Literature Review

Green AI is a concept that has received momentum over the last several years as scholars and professionals have become aware of the environmental implications of large-scale artificial intelligence systems. Conventional deep learning models are intensive to both computation and energy resources and they may cause a huge amount of carbon emission and operational expenses. Green AI is the solution to these problems by encouraging energy-efficient algorithms and efficient use of hardware and sustainable computational methods that reduce environmental impact without sacrificing performance efficiency (Mathew, 2025; Ahmad et al., 2025).

Some of the technological advances that are used to implement energy-efficient deep learning practices are model compression, pruning, quantization, and efficient training models. These methods make computations simpler and more energy-efficient and do not deteriorate the predictive performance greatly. Researchers emphasize that such practices can improve not only the sustainability of the environment but also decrease the costs of operations of the organizations that use AI technologies (Zafar, 2025; Sathio et al., 2025). Also, the combination of AI and energy-efficient infrastructures, including green data centers and smartened cloud computing platforms, will further add to the sustainable computing ecosystems.

Although it can be useful, there are quite a few challenges associated with the implementation of Green AI. Some of the potential technical obstacles that organizations may face include inaccessibility to efficient computing infrastructure, the absence of expertise in particular fields, and the challenge of incorporating energy-efficient patterns in current AI processes. Also, the lack of financial resources and policy backing can deteriorate organizations to invest in sustainable AI technologies (Park, 2025; Das, 2025). These obstacles are especially critical in developing nations where technological facilities and institutional backing of sustainability projects can be in adequate amount.

The other significant aspect of the Green AI discussion is the presence of sustainability awareness and environmental responsibility in organizations. It has been proposed that companies that are highly committed to sustainability and those that care about the environment tend to have high chances of implementing green technologies and energy saving measures. Moreover, technological changes to environmentally friendly systems can be promoted by social consciousness and institutional regulations (Zhao et al., 2025; Qudrat-Ullah, 2025). Thus, the process of awareness and technology preparedness and the impact of organizational strategies on the implementation of Green AI is vital to comprehending how it can be implemented successfully.

Empirical Evidence

A variety of empirical research has been conducted relating to the application of AI to facilitate sustainable energy infrastructure and environmental sustainability. Indicatively, Usman et al. (2025) investigated the attribute of AI-driven technologies in sustainable economic development in Pakistan and they discovered that AI-based innovations can be useful in energy optimization and environmental sustainability where AI-driven green energy solutions are incorporated. Their results highlight the need to integrate technology and be supported by policy in order to accomplish sustainable digital transformation.

In the same manner, Ali et al. (2024) explored the application of artificial intelligence, which enhances sustainability in the Pakistan agriculture and food sector. Their discussion showed that AI applications have the potential to create a robust opportunity to enhance the use of resources and facilitate the activities of a circular economy, yet organizations are commonly confronted with the issues of low level of technical knowledge, inadequate infrastructure, and lack of awareness about sustainable technologies.

Yarally et al. (2023) carried out an empirical research on the subject of energy efficient training in deep learning. Their results have placed the importance of using optimized training methods and effective computation techniques that can save a lot of energy in AI systems. Nevertheless, the research also found a difference between the theoretical progress in Green AI and its practical application in organizations, which implies the necessity to be more aware, trained, and plan how to introduce it to a wider audience.

Hypotheses

H1: Sustainability awareness has a positive impact on the Green AI practices.

H2: Technological preparedness has a positive effect on the use of energy-efficiency deep learning practices.

H3: The issue of financial constraints affects the implementation of Green AI practices adversely.

H4: Sustainability organizational strategies have a positive impact on Green AI practice adoption.

H5: Technological obstacles impact adversely on the adoption of energy-efficient AI systems..

Conceptual Model

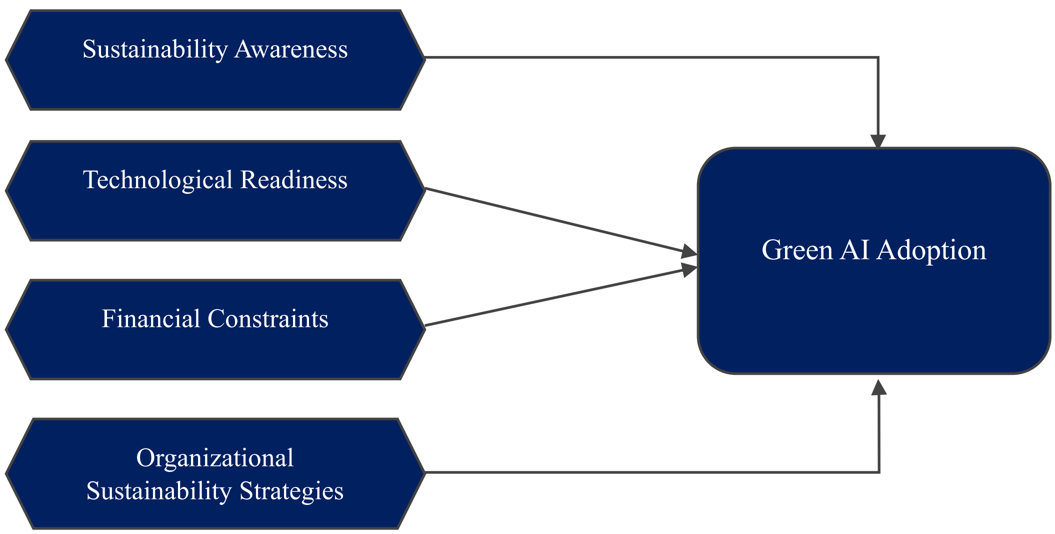


Figure 1. Conceptual Model of the study

Source: formulated after review of existing literature

Methodology

This study adopts a quantitative research approach to investigate the strategies and barriers changing the future of Green AI in the Pakistani technology ecosystem. The study adheres to a positivist Epistemological position and presupposes that determinants of Green AI practice implementation are objective and can be quantified and studied objectively. The survey design used is cross-sectional to gather information about the professionals in 117, but 17 of the questionnaires will lack values hence will not be used in analysis during the development and implementation of the artificial intelligence. This design will be used to define the contemporary perceptions, strategies and obstacles relating to the introduction of energy-efficient deep learning practices in organizations.

The target population will be the AI practitioners, software engineers, data scientists, or IT professionals employed in software houses, AI startups, technology companies, and research institutes in Pakistan. The main data collection tool is the structured questionnaire. The purposive and convenience sampling methods will be used to select the respondents, and they must have the pertinent knowledge or experience in artificial intelligence or machine learning systems. Structural Equation Modeling (SEM) is used to analyze the data with statistical tools like SmartPLS and SPSS to enable the research to investigate the associations among the variables in sustainability awareness, technological preparedness, financial limitations, organizational strategies, and Green AI adoption.

Measures: Multi-item Likert-scale measures are used to measure all constructs in this study with a scale of 1(strongly disagree) to 5 (strongly agree). To achieve reliability and validity, the measurement items are based on the previous research on green technologies, sustainable AI, and energy-efficient computing. The Green AI Adoption construct is used to evaluate the degree to which companies can adopt energy-efficient deep learning methods, sustainable computing approaches, and responsible strategies of developing AI, that are environmentally friendly. Items included in the measurement of this construct are based on the research on sustainable AI and energy-efficient algorithms (Ahmad et al., 2025; Yarally et al., 2023). The Sustainability Awareness construct measures knowledge and the degree of concern practitioners have over the environmental effect of AI systems and the significance of energy-efficient computing. These products are based on the studies of environmental consciousness and adoption of sustainable technologies (Zhao et al., 2025; Qudrat-Ullah, 2025). Technological Readiness is a metric of the presence of infrastructure, computing resources, and technical skills to deploy energy efficient AI systems. The indicators of the measurement are based on the research on technological capability and readiness to implement AI (Park, 2025; Sathio et al., 2025). The Financial Constraints construct measures perceived cost impediments in the use of energy-saving infrastructure, hardware optimization, and sustainable computing infrastructure. These products are based on the research on obstacles to the introduction of sustainable technologies and energy-efficient systems (Das, 2025; Ali et al., 2024). Last but not the least, Organizational Sustainability Strategies evaluate the degree to which firms have policies, initiatives or strategic frameworks that facilitate the development of AI in a sustainable environmental manner. The products are based on the researches analyzing the sustainability strategies and AI-based green innovations (Usman et al., 2025; Zafar, 2025).

Demographic Profile of the Respondents.

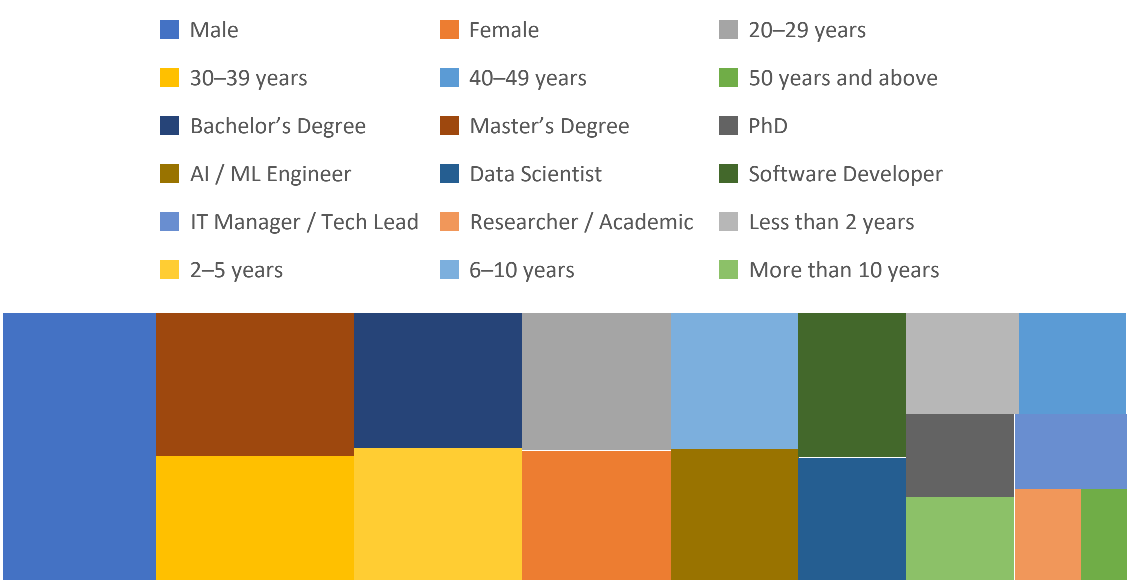
The demographic traits of respondents are relevant in the survey-based research because it includes the information about the background of research participants and the potential assessment of whether a sample is a proper representation of the required population. The demographic data that was used in this study was gathered among AI practitioners and technology professionals in the technology ecosystem of Pakistan. The demographic data consisted of gender, age category, educational level, profession, and years of experience in AI or other technologies. These attributes serve to learn about the variety and the level of expertise of the respondents who adopt the energy-efficient deep learning practices.

Table 1 Demographic Profile of Respondents

DEMOGRAPHIC VARIABLE	CATEGORY	FREQUENCY	PERCENTAGE (%)
GENDER	Male	68	68%
	Female	32	32%
AGE GROUP	20–29 years	34	34%
	30–39 years	41	41%
	40–49 years	18	18%
	50 years and above	7	7%
EDUCATIONAL QUALIFICATION	Bachelor's Degree	38	38%
	Master's Degree	47	47%
	PhD	15	15%
PROFESSIONAL ROLE	AI / ML Engineer	28	28%
	Data Scientist	22	22%
	Software Developer	26	26%
	IT Manager / Tech Lead	14	14%
	Researcher / Academic	10	10%
EXPERIENCE IN AI / TECHNOLOGY	Less than 2 years	19	19%
	2–5 years	37	37%
	6–10 years	29	29%
	More than 10 years	15	15%

The demographic data reflects that most participants are male (68 percent), with 32 percent being female as the gender representation in the technological and AI industry tends to be. Regarding the age range, the highest respondent segment is 30-39 years (41%), then 20-29 years (34%), which implies that the majority of participants are young to middle-aged professionals who are still in their career and actively working in the field of AI. In terms of the educational level, a significant percentage of the respondents have Master degrees (47%), which suggests that the level of academic background of specialists working with artificial intelligence technologies is relatively high..

Figure 2. Demographic Profile of Respondents



Moreover, it is also indicated that the distribution of professional roles demonstrates that most respondents are engineers working in AI models (28%), software (26%), and data (22%) specialists, which means that the sample is represented by specialists working directly on the development and implementation of AI models. With regards to experience, they have 25 years (37% of the respondents) of experience and 610 years (29% of the respondents) of experience, which proves that the majority of the participants have practical experience with AI technologies and digital innovation. In general, the demographic data indicates that the respondents are well-informed with the pertinent work experience and technical skills to be included in the study as the participants of investigating the strategies and obstacles to the Green AI implementation in the Pakistani technology environment.

Descriptive Statistics of the Study Variables.

The central tendency and dispersion of the variables used in the study is summarized using descriptive statistics. A survey-based research design allows the researcher to use the mean value, which refers to the average perception of the respondents with regard to a construct, and the standard deviation (SD) which is the variation or the looks of the responses around the mean. Greater mean values usually imply the increased level of consensus among respondents on the statements that are used to measure a construct. The descriptive statistics will be done on the main constructs such as Green AI Adoption, Sustainability Awareness, Technological

Readiness, Financial Constraints, and Organizational Sustainability Strategies in this study.

Table 2 Descriptive Statistics of Study Variables

VARIABLE	NUMBER OF ITEMS	MEAN	STANDARD DEVIATION
SUSTAINABILITY AWARENESS	4	3.92	0.71
TECHNOLOGICAL READINESS	4	3.68	0.76
FINANCIAL CONSTRAINTS	4	3.41	0.83
ORGANIZATIONAL SUSTAINABILITY STRATEGIES	4	3.74	0.69
GREEN AI ADOPTION	4	3.85	0.72

According to the findings of Table 2, the highest mean value of the studied variables is Sustainability Awareness (Mean = 3.92, SD = 0.71), which implies that a respondent has a relatively strong awareness of the environmental impact of artificial intelligence and the need to practice regarding the importance of energy-efficient computing. On the same note, Green AI Adoption (Mean = 3.85, SD = 0.72) also presents a rather high mean, which means that the organizations belonging to the technology ecosystem of Pakistan are slowly adopting the use of energy-efficient deep learning and sustainable AI over time.

The results also show that the Strategies of Organizational Sustainability (Mean = 3.74, SD = 0.69) and Technological Readiness (Mean = 3.68, SD = 0.76) have moderate to high scores indicating that most organizations are establishing strategic plans and technological potentials to enable sustainable implementation of AI. Nonetheless, the Financial Constraints (Mean = 3.41, SD = 0.83) presents significantly reduced mean values with somewhat increased dispersion that implies that barriers and investment challenges based on costs are still significant barriers to the application of Green AI practices on a large scale. Overall, based on the descriptive statistics, it can be concluded that although the level of awareness and organizational commitment to sustainable AI is growing, there are certain financial and technological constraints, which can influence the rate of Green AI implementation.

Reliability Analysis of Constructs

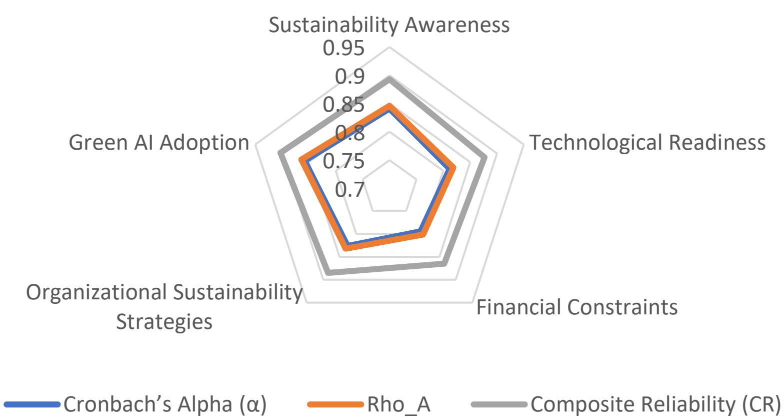
Reliability analysis is done to determine the internal consistency of the measurement constructs employed in the study. Cronbachs Alpha (0), Rho A and Composite Reliability (CR) are typically used to assess reliability in structural equation modeling and specifically in PLS-SEM. Cronbachs Alpha tests the internal consistency of a construct of items and Rho A is taken to be a more precise estimate of reliability in PLS-SEM. Composite Reliability measures the reliability of the latent constructs in the model of measurement. Based on generally accepted scales, anything more than 0.70 means satisfactory reliability range with anything between 0.60 and 0.70 being found as acceptable in exploratory studies.

Table 3. Reliability Analysis of Constructs

VARIABLE	CRONBACH'S ALPHA (Α)	RHO_A	COMPOSITE RELIABILITY (CR)
SUSTAINABILITY AWARENESS	0.841	0.846	0.893
TECHNOLOGICAL READINESS	0.812	0.819	0.877
FINANCIAL CONSTRAINTS	0.794	0.801	0.865
ORGANIZATIONAL SUSTAINABILITY STRATEGIES	0.826	0.832	0.885
GREEN AI ADOPTION	0.858	0.864	0.903

Table 3 results show that the levels of constructs reliability are satisfactory. The Alpha level of the Cronbach coefficients varies between 0.794 and 0.858 which implies that the measurement items within each construct are highly consistent. On the same note, the values of the Rho A are between 0.801 and 0.864 and this again certifies the dependability of the measurement model and also means that the indicators are always reflecting their respective latent constructs.

Figure 3. Reliability Analysis of Constructs



Moreover, Composite Reliability (CR) values are between 0.865 and 0.903, which is more than the suggested value of 0.70. These findings confirm that the measurement items are reliable to measure the constructs incorporated in the research. To sum up, the results of the reliability analysis show that scales of the measurement of Sustainability Awareness, Technological Readiness, Financial Constraints, Organizational Sustainability Strategies, and Green AI Adoption have sufficient internal consistency and can be examined further in the structural model.

Outer Loadings of Measurement Items

The outer loadings are considered to determine the reliability of individual items of measurement that belong to each construct in the measurement model. In PLS-SEM analysis, the value of outer loading shows how well an observed variable reflects its latent construct. By the set rules, the values of the outer loading that are above the mark of 0.70 are regarded as a good value because this means that the indicator is sharing a large portion of variance with the construct. Items whose loadings are just under this value can also be retained provided they bring value to the theoretical meaning of the construct and the overall reliability measures are satisfactory.

Table 4 Outer Loadings of Measurement Items

ITEMS	SA	TR	FC	OSS	GAI
SA1	0.812				
SA2	0.845				
SA3	0.834				
SA4	0.801				
TR1		0.796			
TR2		0.824			
TR3		0.842			
TR4		0.809			
FC1			0.771		
FC2			0.804		
FC3			0.826		
FC4			0.788		
OSS1				0.817	
OSS2				0.846	
OSS3				0.832	
OSS4				0.801	
GAI1					0.853
GAI2					0.871
GAI3					0.846
GAI4					0.824

Table 4 results show that all measurement items have satisfactory values of outer loading on their constructs. The loading values are between 0.771 and 0.871 and they are above the recommended loading of 0.70. This means that it is important to note that every indicator plays a vital role in explaining its construct. In addition, the table has a diagonal structure showing that each item loads highly on its desired construct hence validity of the measurement indicators. All in all, the outer loading analysis indicates the reliability of the indicators selected by the study and suggests that they also sufficiently measure their underlying latent constructs. Because all the items show high loading as well as have conformed to their theoretical constructs, they are retained to be further analyzed in both measurement and structural models.

Measurement and Structural Model Summary

Once the validity of reliability and indicator validity are determined, one should examine convergent validity, discriminant validity, effect sizes, and predictive power of constructs in the model. Average Variance Extracted (AVE) is used to evaluate the convergent validity, which is the amount of variance explained by a construct as compared to measurement error and a range of 0.50 and above. The discriminant validity (HTMT) is used to demonstrate that the constructs are empirically different and the value of f 2 effect size measures the effects of an independent variable on a dependent variable, the value of f 2 effect size can be interpreted as small (0.02), medium (0.15), and large (0.35). At last, R 2 is the fraction of variance that the independent variables account for in the dependent variable, and the closer it is to 1, the better the predictive value of the independent variables.

Table 5 AVE, Discriminant Validity (HTMT), f^2, and R^2 of Constructs

CONSTRUCT	AVE	HTMT (VS GAI)	F^2 (IMPACT ON GAI)	R^2
SUSTAINABILITY AWARENESS (SA)	0.682	0.671	0.142	0.632
TECHNOLOGICAL READINESS (TR)	0.683	0.654	0.118	0.632
FINANCIAL CONSTRAINTS (FC)	0.641	0.532	0.092	0.632
ORGANIZATIONAL SUSTAINABILITY STRATEGIES (OSS)	0.689	0.598	0.128	0.632
GREEN AI ADOPTION (GAI)	0.726	-	-	-

According to the results shown in Table 5, all constructs have satisfactory convergent validity with the AVE values between 0.641 and 0.726, which is higher than the suggested value of 0.50. This is an assurance that the measurement items are adequate to measure the underlying constructs. The values of the independent variables of all the independent variables in relation to the Green AI Adoption are less than 0.85 indicating that there is adequate discriminant validity and that each construct is used to measure a different facet of the theoretical model.

The f 2 effect size indicates that Sustainability Awareness (0.142) and Organizational Sustainability Strategies (0.128) are moderate in their effect on Green AI Adoption, and Technological Readiness (0.118) and Financial Constraints (0.092) have small to moderate effects. This implies that awareness and organizational strategy are more influential in determining adoption as compared to technological or financial elements. The value of R 2 = 0.632 shows that the independent variables together explain a large share of variance in Green AI Adoption equal to around 63 percent, which is a good predictor of the model. On the whole, these findings confirm the measurement and structural models and give assurance in the future hypothesis testing.

Path Coefficient Analysis

PLS-SEM path coefficient analysis is used to measure the strength, direction and significance of the relationship between independent and dependent variables. The coefficients reveal the degree to which every predictor influences the dependent variable whereas t-values and p-values reveal the level of statistical significance. In PLS-SEM, t-values of 1.96 and p-values of less than 0.05 signify that the path is statistically significant at the 5 percent level (Hair et al., 2022). This analysis is essential in order to test the study hypotheses about the effects of Sustainability Awareness, Technological Readiness, Financial Constraints, and Organizational Sustainability Strategies on the Green AI Adoption.

Table 6. Path Coefficient Analysis (PLS-SEM Results)

PATH	PATH COEFFICIENT (B)	T-VALUE	P-VALUE
Sustainability Awareness → Green Ai Adoption	0.361	4.72	0.000
Technological Readiness → Green Ai Adoption	0.289	3.86	0.000
Financial Constraints → Green Ai Adoption	-0.217	2.94	0.003
Organizational Sustainability Strategies → Green Ai Adoption	0.335	4.21	0.000

Table 6 results suggest that Green AI Adoption is positively and statistically significantly influenced by Sustainability Awareness (β = 0.361, = 4.72, = 0.001), which is in support of H1. This is an indication that the more AI practitioners are aware of AI practices related to the environment and energy efficiency, the more they embrace Green AI. In the same manner, Technological Readiness shows a significant and positive impact (β = 0.289, t = 3.86, p < 0.001), which confirms H2 that organizations that have superior infrastructure, tools and technical skills have a higher likelihood of adopting energy-efficient deep learning.

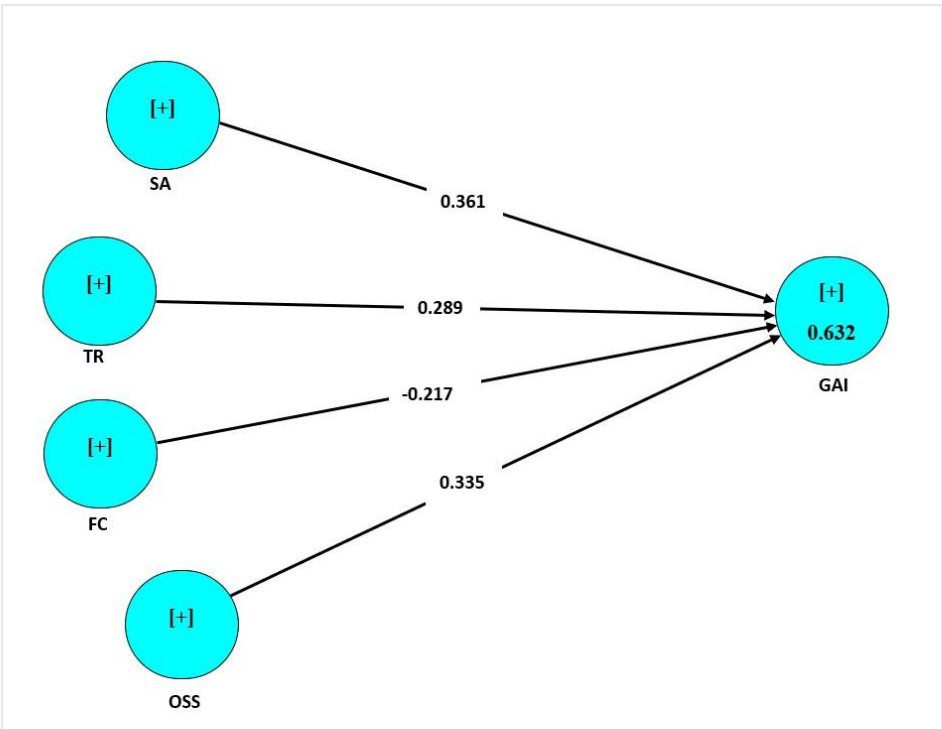


Figure 4. SEM Model of the Study

Financial Constraints significantly influence Green AI Adoption (β = -0.217, t = 2.94, p = 0.003), which confirms H3, that perceived cost barriers are higher, and, therefore, the sustainability AI-based technologies are less likely to be implemented. Lastly, Organizational Sustainability Strategies have a positive impact on Green AI Adoption (β = 0.335, t = 4.21, p =0.001) confirming H4, which predicts the significance of strategic policies and commitment to sustainability in the organization in supporting energy-saving AI adoption. In general, the path coefficient analysis shows that the proposed relationships are significant and can be considered in theory in terms of the factors and obstacles of Green AI implementation in the ecosystem of technology in Pakistan.

Discussion
The results of the present study reveal that the Sustainability Awareness, Technological Readiness, Financial Constraints, and Organizational Sustainability Strategies are important factors that determine whether AI practitioners in the Pakistani technology ecosystem adopt Green AI practices or not. In particular, the strongest predictor was the Sustainability Awareness, which emphasizes that the knowledge and interest of practitioners in the environmental effects of AI are significant stimuli to promote the practice of energy efficiency (Zhao et al., 2025; Ahmad et al., 2025). The technological preparedness is also essential, which means that availability of efficient infrastructure and computational facilities and competent staff make it possible to implement energy efficient deep learning models (Park, 2025; Sathio et al., 2025). On the other hand, Financial Constraints has a negative effect on adoption, indicating that monetary barriers continue to be a major challenge to those organizations that aim to adopt Green AI (Das, 2025; Ali et al., 2024). Also, the fact that Organizational Sustainability Strategies are present supports the prioritization of institutional commitment and strategic frameworks when developing environmental responsible AI (Usman et al., 2025; Zafar, 2025). These findings are similar to the existing literature that focuses on the role of awareness, organizational capacity, and resource availability in promoting the idea of sustainable technology adoption (Yarally et al., 2023; Mathew, 2025).

Recommendations
In response to the results, organizations need to give more emphasis on training programs and workshops to increase Sustainability Awareness among AI practitioners to emphasize the environmental and energy-related consequences of AI implementation. Technological Readiness should be reinforced by encouraging investment in energy efficient computing infrastructure and optimal algorithms. All these can be offered by the policymakers and industry stakeholders to reduce the financial obstacles that dwarf the adoption of Green AI. Besides, the organizations are to create and institutionalize sustainability policies, including an environmental factor in the corporate policies, AI development procedures, and project management systems to achieve long-term sustainability and adherence to international sustainability standards.

Implications
Practical and theoretical implications of the study exist. In practice, it will offer the technology companies, startups, and research centers in Pakistan with practical insights into the motivation and obstacles of Green AI adoption to allow the organization to create a successful strategy of a Green AI adoption. In theory, the research makes a contribution to the newly developing literature in sustainable AI and green computing in that it empirically confirms a conceptual framework that interprets awareness and technological preparedness and financial limitations and alignment with organizational strategies to Green AI adoption in a developing country setting (Ahmad et al., 2025; Usman et al., 2025; Yarally et al., 2023). This fact expands knowledge regarding the implementation of AI practices that are environmentally friendly in the form of the emerging economies.

Limitations
There are some limitations in this study, which must be noted. To start with, the cross-sectional survey design records the responses at a particular time, which indicates that it is impossible to determine the changes in the adoption of Green AI over time. Second, the sample is limited to the AI practitioners and professionals in Pakistan, which can reduce the applicability of the results in other countries or industries. Third, the research is based on self-reports, and thus, it can be prone to bias on responses, particularly on awareness perceived, financial barriers, or organizational practices. Lastly, although the predictor factors are considered essential, other possible alternatives like regulatory frameworks, collaboration of the

industry, or cultural influences were not considered and can contribute to adoption.

Future Research Directions

Future studies can take a longitudinal design to investigate the dynamics of Green AI implementation over time and the interplay of the awareness, resources, and strategies. The comparative analyses of various nations or sectors might give some information about the contextual variations in the use of energy-efficient AI practices. Also, the qualitative methodology might be included in the future research to learn more about the organizational decision-making process, obstacles, and the effective implementation of AI to be sustainable. The exploration of regulatory support, environmental policies, and stakeholder collaboration as other predictors can further improve the knowledge on factors contributing to Green AI adoption.

Conclusion

This paper explored the policies and obstacles that affect the adoption of Green AI in the Pakistani technology ecosystem with reference to Sustainability Awareness, Technological Readiness, Financial Constraints, and Organizational Sustainability Strategies. The results affirm that awareness, organization strategies, and technological readiness have a positive impact on the adoption, whereas financial constraints have a negative impact on the implementation. These findings demonstrate the significance of the dissemination of knowledge, strategic planning, and resource allocation to achieve the promotion of energy-efficient practices of deep learning. The empirical validation of such relationships is what makes the study add to the body of literature on sustainable AI and offers a powerful framework of understanding adoption drivers in emerging economies (Ahmad et al., 2025; Yarally et al., 2023; Usman et al., 2025).

In general, the paper points out that the implementation of Green AI is not merely an issue of technology but also organization and strategies. Companies that take the initiative to invest in awareness programs, infrastructure, and sustainability initiatives can increase their uptake of energy-efficient AI, lessen their effects on the environment, and gain long-term operational as well as social gains. The findings can be used by policymakers and industry stakeholders to come up with favorable frameworks, monetary incentives, and training programs that will help in the sustainable adoption of AI in the Pakistani technology sector.

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