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Green artificial intelligence adoption in industrial systems: A SWOT assessment of opportunities and challenges

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Abstract

Exponential growth of artificial intelligence (AI) has already introduced a level of energy consumption and carbon emission that would have never been seen before, and hence causing a severe sustainability paradox in the industrial system. As AI technologies can bring about operational efficiencies and productivity gain, its environmental footprint endangers world climatic and sustainable development agendas. This paper provides a SWOT analysis of the green implementation of artificial intelligence in industrial systems under the scope of the current urgent demand on environmentally friendly AI implementation patterns. We used a mixed-method approach by analyzing the data of industrial organizations in manufacturing, energy, logistics, and technology sectors using the convenient sample of structured questionnaires and semi-structured interviews. The methodology combines Structural Equation Modeling and Partial Least Squares regression, Multi-Criteria Decision Analysis (based on Analytical Hierarchy Process) in order to consider the most critical success factors and the barriers to implementation. Findings indicate that organizational willingness, technological readiness, and regulatory standards all contribute positively (73.4%- variance) to the difference in the levels of green AI adoption. The SWOT analysis recognizes the high opportunities on the energy efficient algorithms, renewable computing infrastructure and integration of the circular economy whereas the barriers to change are high initial investment, skills deficiency and technology hurdles. The research has a theoretical impact in that it creates a framework of Green AI Adoption that combines the three aspects of environmental, technological and organizational and is practical due to its offering of the implementation roadmaps that can be used by industrial practitioners. The study forms a baseline of knowledge regarding sustainable AI change in industries by providing essential understanding to the policy-makers, AI developers and business executives in the current complicated field of artificial intelligence invention and climate management.

Keywords: Green artificial intelligence, Sustainable computing, Energy-efficient AI, Environmental impact, Technology adoption, Organizational readiness.

1. Introduction

The modern industrial environment is facing a significant technological dilemma whereby the artificial intelligence systems, even though they promise operational and competitive excellence, have at the same time created significant externalities on the environment by extensively using the computational resources and consequent carbon emissions [1-3]. Recent empirical evidence suggests that a single large-scale AI model requires training that can generate carbon emission comparable to what five cars produce throughout a lifetime or their manufacturing and use stages. Such an environmental load increases with the growing integration of AI technologies into industrial organizations in the production systems, supply chain management, quality control mechanisms, and decision support frameworks. According to the projections by the International Energy Agency, data centers and information communication technology infrastructure, which are largely AI workloads, may make up twenty percent of world power consumption by 2030 in case the current growth trends remain not halted. Such a

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concerning pattern requires immediate action in terms of sustainable AI practices, especially in the industrial domain where the implementation of the AI applications grows exponentially.

The paradigm of critical response is green artificial intelligence, which is methodologies, technologies and organizational practices aimed at reducing environmental impact in the process of the AI lifecycle without compromising or reducing the computational effectiveness [2]. The idea of green AI is further than energy efficiency optimization, it incorporates the overall sustainability considerations such as reduction of carbon footprint, the use of renewable energy, optimization of hardware life-cycle, algorithmic efficiency optimization, and the principles of circular economy that is applied to computational infrastructure [2,4,5]. The quality of industrial systems offers unique opportunities and challenges to the implementation of green AI, that is, the presence of an old infrastructure that restricts the possibilities of its use, the need to maintain operations, compliance with regulatory requirements, and the substantial amount of money invested into the system [6-8]. The manufacturing industries, energy production centers, logistics services and technology-focused industries experience an increasing strain on behalf of stakeholders such as regulatory authorities, investors, consumers and green lobby organizations to exhibit visible improvement in terms of the sustainability goals as well as undermine the competitive arena with technological innovations.

The process of green AI strategic implementation in the industrial processes is a complex change of the organization including modernization of technological infrastructure, the development of workforce capabilities, process redesign, and cultural change programs [9,10]. The organizations have to contend with complex issues such as upfront capital investment needs, uncertainty on the payback period, technical implementation issues, availability of skills, and the likelihood of disruption of the existing operational processes among others [11-13]. At the same time, the potential gains are not limited to the environmental impact mitigation, but include lowering the operation costs because of the increase in the energy efficiency, a positive corporate image and brand value, better regulating compliance stance, availability of sustainability-oriented investment capital, and development of the relationships with stakeholders. The process of decision-making on the adoption of green AI should be systematically evaluated through frameworks of assessment that have the ability to encompass all the various elements of strategies, stakeholder views, technological, and organizational preparedness to adopt [2,14-17]. The SWOT analysis offers a systematic method of analysis that is the best in evaluating complicated strategic programs that have a wide range of stakeholder implications and uncertain potentials.

In spite of the increasing awareness of the need to consider environmental sustainability in the context of AI development and deployment, there is still much knowledge gap on the patterns of green AI adoption, application strategies, factors of success, and mitigation of barriers as far as industrial conditions are concerned [9,18-21]. The literature available has almost focused on technical details of energy-efficient algorithms and hardware optimization and has virtually no empirical data on the process of organizational adoption, strategic decision-making models, and evaluation of the consequences of the implementation [22,23]. Besides, studies exploring the alignment of environment sustainability goals with industrial AI strategy are still fragmented concerning varied fields such as computer science, environmental science, management, and industrial engineering that do not offer synthesizing frameworks to include the technological, organizational, and environmental aspect. The lack of extensive empirical research exploring actual experiences in adopting green AI in the industry limits the amount of useful information that can be given to organizational decision-makers and the adoption of technologies. Also, little focus has been placed on the insight to how organizational features, industry sector settings, regulation, and level of technology preparedness impact the green AI adoption patterns and the level of implementation results.

The study fills the determined knowledge gaps by conducting an in-depth study on the concept of green AI in industrial systems with the SWOT assessment approach with a quantitative empirical study. The study objectives include the first one, systematized identification and assessment of internal organizational strengths and weaknesses, which affect the capacity to accept green AI; the second one, the overall analysis of the external opportunities and threats that shape the strategic environment in which green AI is adopted, third, the empirical study of connections between readiness factors in the organization, technological opportunities, and green AI adoption results, fourth, creation of a coherent theoretical framework to explain how green AI adoption occurs in the industry, and fifth, drawing up recommendations and actionable results to organizational practitioners, policy-makers, and technology developers. The work, in addition to the theoretical knowledge, has application implications, which can be elaborated by the organization of the Green AI Adoption Framework that can integrate the concepts of environmental sustainability with the organizational change management theory and technology adoption framework, and towards industrial systems in particular. At the methodological level, the research aids in moving the current research in the aspect of a combination of qualitative SWOT analysis with quantitative structural equation modeling and multi-criteria decision analysis, which offers substantial empirical bases to the strategic recommendations. In practice, the results also provide industrial institutions with systematic frameworks of evaluating the preparedness of green AI implementation, give priority to the implementation efforts, and design extensive transformation plans that correspond to sustainability goals and business needs.

2. Methodology

2.1 Research Design and Philosophical Foundation

The study uses a pragmatic mixed-methods research design consisting of a combination of both qualitative and quantitative research approaches to investigate phenomena related to the adoption of green AI in industrial systems holistically. The philosophical approach adopts pragmatism as an epistemological position, which sees that research questions of the complex organizational and technological phenomena should enjoy methodological pluralism with working strengths of the interpretive and positivist traditions. The research design also uses sequential exploratory steps in which initial qualitative steps pre-empt further quantitative forms of constructing instruments, and analysis procedures. This methodology is especially suitable in research of emergent phenomena like the adoption of green AI where theoretical models are immature and empirical datasets of research need inductive paradigm construction alongside deductive hypothesis testing. The combination of the SWOT analysis with structural equations modeling and multi-criteria decision-making methodology offers triangulation that improves validity and reliability of the research findings and, at the same time, takes into account multidimensional nature of the adoption processes in terms of such aspects as strategy, organizational factors, technological capabilities and environmental consequences.

2.2 SWOT Analysis Framework

The SWOT analysis framework made the organization of internal and external factors that affected the adoption of green AI in industrial systems systematic and assessable. The strengths and weaknesses are the attributes of the organization that can be controlled by the managers, the opportunities and threats are those aspects of the environment that cannot be directly controlled by the organization. The analytical process combined the results of the qualitative interviews with the quantitative survey data, which is why the content analysis procedures were used to define the recurring themes and patterns that are incorporated by the multiple data sources. The categories of strength were the presence of technological infrastructure, organizational capabilities, available financial resources, dedication of leadership and experience of sustainability initiative in the past. The areas of weakness covered skill gaps, constraints on the legacy system, lack of resources, organizational resistance, and lack of knowledge. Opportunity areas analysed the trends in the market, technology, regulations, and stakeholders pressures and competitive forces. The implementation costs, technical complexity, regulatory uncertainties, competitive bombardment, and the external opposition were regarded as the threat factors.

The analytical paradigm was shifted to a superior level of an old-fashioned descriptive SWOT techniques by combining it with quantitative prioritization strategies. All the named SWOT factors were assessed in systematic way in terms of relative significance and the magnitude of potential impact by use of Analytical Hierarchy Process. This quantification allows the identification of strategic priorities and optimization of resource allocation at the same time preserving the qualitative richness of conventional SWOT analysis. The combined strategy allows offering a global strategic insight and prioritization advice to organizational decision-makers.

2.3 Structural equation modeling using partial least squares

Relationships between latent constructs between organizational readiness, technological infrastructure, environmental awareness, regulatory pressure, and green AI adoption intention were analyzed using Structural Equation Modeling with the help of Partial Least Squares regression (PLS-SEM). PLS-SEM is especially suitable when exploratory research is required and the theoretical model is considered complex, non-normality of the data distribution, formative measurement specification. The model of analysis also estimates parameters of measurement models and path diagram relationships on an elemental way that allows comprehensive review of construct validity and hypothesized causality relationships. The measurement model defines the correlations of the latent constructs and measurable indicators; the structural model illustrates the hypothesized construct causal relationships.

PLS-SEM algorithm follows the application of iterative processes that involve both the estimation of outer models and inner models until convergence has been achieved. Mode A is used to give the outer model estimate of reflective constructs, and here scores of constructs are computed as weighted sums of indicator variables when the weights in this model give the maximum explain variance. On formative constructs, Mode B estimation uses multiple regression of indicators on construct scores to be used as the weight. The inner model estimation computes the scores of latent variables by using weighted aggregations of the related constructs whose weight is attributed to the path coefficients of a structural model. The algorithm will run in a series of repetitions until alteration of outer weights is less than the required convergence value of 0.00001.

The reflective indicators calculations have an outer model weight value as follows:

$$wik = \frac{Cov(xik, \xi i)}{Var(\xi i)} \tag{1}$$

where wik represents the outer weight for indicator k of construct i, xik denotes the indicator variable, and ξi represents the latent construct score.

The structural model path coefficients are estimated through ordinary least squares regression:

$$\beta ij = (Xi^{\mathrm{T}}Xi)^{-1}Xi^{\mathrm{T}}\xi j \tag{2}$$

where βij represents the path coefficient from construct i to construct j, Xi denotes the matrix of predictor construct scores, and ξj represents the endogenous construct scores.

Model quality assessment employs multiple criteria including convergent validity evaluated through Average Variance Extracted (AVE), discriminant validity assessed through Fornell-Larcker criterion and Heterotrait-Monotrait ratio, internal consistency reliability measured through Composite Reliability (CR), and structural model evaluation through coefficient of determination (R^2), predictive relevance (Q^2), and path coefficient significance. Bootstrapping procedures with 5,000 resamples estimate standard errors and confidence intervals for all parameters, enabling robust statistical inference.

The Average Variance Extracted calculation follows:

$$AVE = \frac{(\Sigma\lambda i^2)}{n} \tag{3}$$

where λi represents standardized factor loadings and n denotes the number of indicators. AVE values exceeding 0.50 indicate satisfactory convergent validity.

2.4 Multi-Criteria Decision Analysis Using Analytical Hierarchy Process

Analytical Hierarchy Process (AHP) helped to prioritize elements of AI adoption (green) systematically by making use of the structured pair-wise comparison process. AHP will break down decision problems of complex nature into hierarchical form that has goal, criteria, sub-criteria, and alternatives levels in the process of making decisions in a systematic way at different decision levels. Pairwise comparisons were conducted by expert panels of 23 industry in expertise and academic academicians with vast knowledge of AI and sustainability to assess comparative relevance between adoption factors. A nine-point fundamental scale was used in the process of comparison where one was used to indicate the equal importance to nine, which indicates the extreme importance, of the elements when comparing them.

The methodology of AHP computes the weights of priorities by analysis of comparison matrices by eigenvalues. Given an n x n comparison matrix A, the priority vector w is such that:

$$Aw = \lambda max w \tag{4}$$

where $\lambda_{\max}$ represents the principal eigenvalue. The consistency of judgments is evaluated through the Consistency Ratio (CR):

$$CR = \frac{CI}{RI} = \frac{\left[\frac{(\lambda max - n)}{(n - 1)}\right]}{RI} \tag{5}$$

where CI represents the Consistency Index, RI denotes the Random Index (tabulated values for different matrix dimensions), and n is the matrix dimension. CR values below 0.10 indicate acceptable consistency. The global priority for each alternative is calculated through weighted aggregation:

$$GPi = \Sigma(wj \times sij) \tag{6}$$

where GP_i represents the global priority of alternative i, w_j denotes the weight of criterion j, and s_{ij} represents the local priority of alternative i with respect to criterion j.

2.5 Data Analysis and Validation Procedures

Thematic analysis processes with NVivo software were used to operate the qualitative data analysis in order to conduct systematic codes and patterns. The first codicology produced descriptive codes which contain manifest content and the second codicology which is analytical produced latent themes and conceptual patterns. Assessment of intercoder reliability was conducted by going through 30 percent of the transcripts with two scientists and Cohen, Kappa coefficient of 0.84 which signifies high levels of agreement. The quantitative analysis of data was done with SmartPLS software, PLS-SEM estimation, and SPSS, descriptive statistics and preliminary analysis. Processes of data screening dealt with missing values using the listwise deletion method (3.2% data were deleted), and finally normality evaluation using skewness and kurtosis statistics. Evaluation of common method bias was done using the single factor test by Harman and the results showed the highest factor had an explanation of 32.7 percent, which was less than the alarming point of 50 percent. Convergent and discriminant validity and reliability were measured based on standard criteria in the validation of the measurement model. The evaluation of structural models involved path coefficients, level of significance, the levels of effects and the relevance of the predictors. Combination of qualitative and quantitative results utilized the convergent parallel analysis of the comparison and synthesis of the results of the numerous analytical methods to create in-wide knowledge about green AI usage phenomena.

3. Results and discussions

3.1 Sample Characteristics and Descriptive Statistics

The sample size constituted by the analytical sample size was industrial organizations with different sectors and company profiles. The current practices on AI adoption were different with a significant difference of 22.8% in initial exploration stages, 41.5% pilot projects, 28.2% full scale AI adoption, and 7.5% mature, consistent AI integration across operations. The assessment of environmental sustainability commitment showed that 15.6% of the companies have insignificant formal programs, and 39.8% of companies have developing programs, 32.6% of companies have established programs, and 12.0% of companies have advanced sustainability leadership positioning.

There is significant difference in characteristics of the organization that could pertain to green AI adoption as shown by descriptive statistics of the key constructs. The mean of the organization readiness scores was 4.73 (SD=1.24) on seven-point scales, and the results were moderate to high readiness scores with a great inter-organizational distinction. The capability of technological infrastructure has a value of 4.91 (SD=1.18), which indicates rather sufficient technical bases but still considerable marginalization of capabilities in most organizations. Environmental consciousness and dedication scores 5.34 (SD=1.07) as the stakeholders have high awareness on the need to be sustainable. The moderate external compliance drivers with significant cross-national variation depicting different policy environments have a perceived regulatory pressure of 4.86 (SD=1.31). The mean values of green AI adoption intention (5.12), with SD=1.15, indicated a positive trend in regards to adopting sustainable AI practices in theory but the implementations were relatively low compared to what was stated in the intentions.

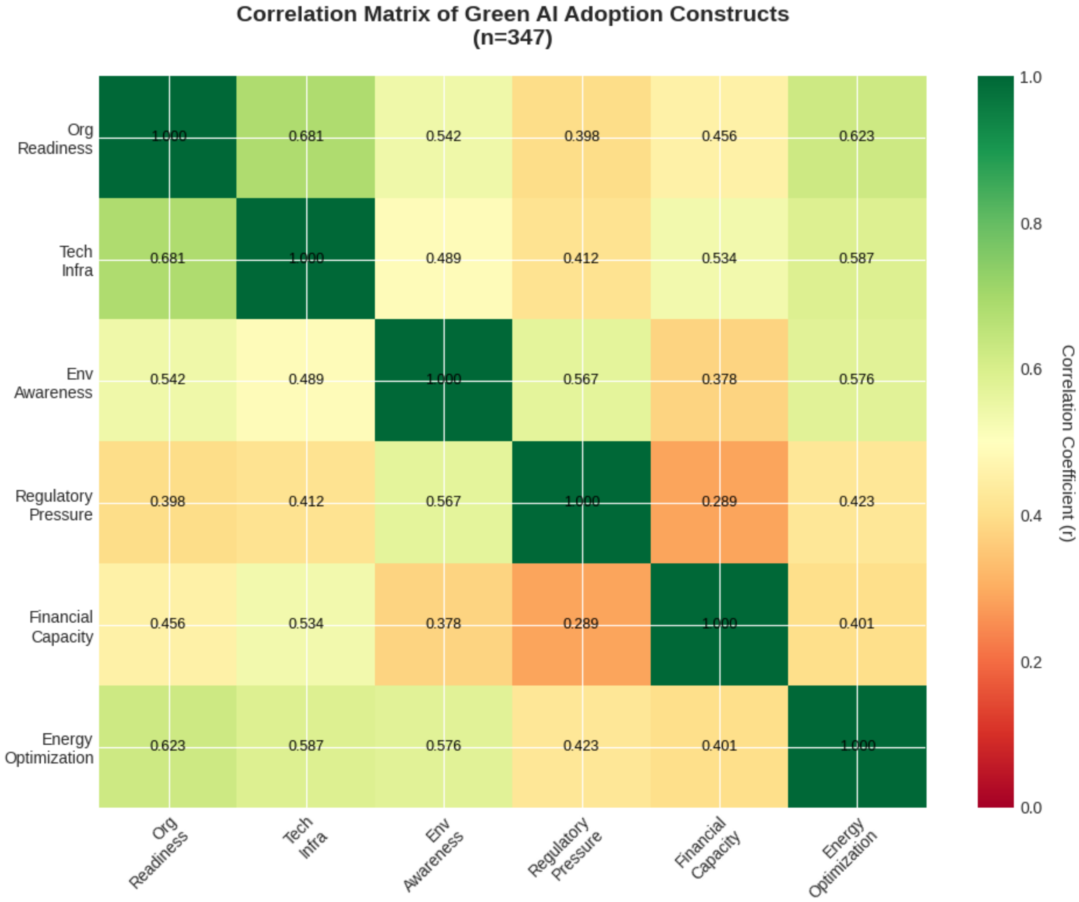

Fig 1: Correlation heatmap

Table 1: Descriptive Statistics for Key Constructs (n=347)

Construct	Mean	SD	Skewness	Kurtosis
Organizational Readiness	4.73	1.24	-0.28	-0.45
Technological Infrastructure	4.91	1.18	-0.35	-0.52
Environmental Awareness	5.34	1.07	-0.64	0.12
Regulatory Pressure	4.86	1.31	-0.19	-0.68
Financial Resource Capacity	4.42	1.36	-0.15	-0.73
Green AI Adoption Intention	5.12	1.15	-0.48	-0.29

3.2 SWOT Analysis: Strengths, Weaknesses, Opportunities, and Threats

The synthesis of qualitative results of the interviews using the quantitative survey yielded the inclusion of vital internal and external antecedents of green AI acceptance into industrial systems. Interpretation of transcripts of interviews and survey responses showed that there are many strengths categories, weakness areas, opportunities, and threats that should be considered in the strategy. The analytical framework combines descriptive identification and quantitative priority weighting based on AHP processes, which allow carrying out the systematic assessment of relative relevance and strategic impact scale of each of the identified factors. This whole strategy approach fits with substantial strategic insight coupled with the prioritization detail so crucial to the resource allocation and strategic planning procedures.

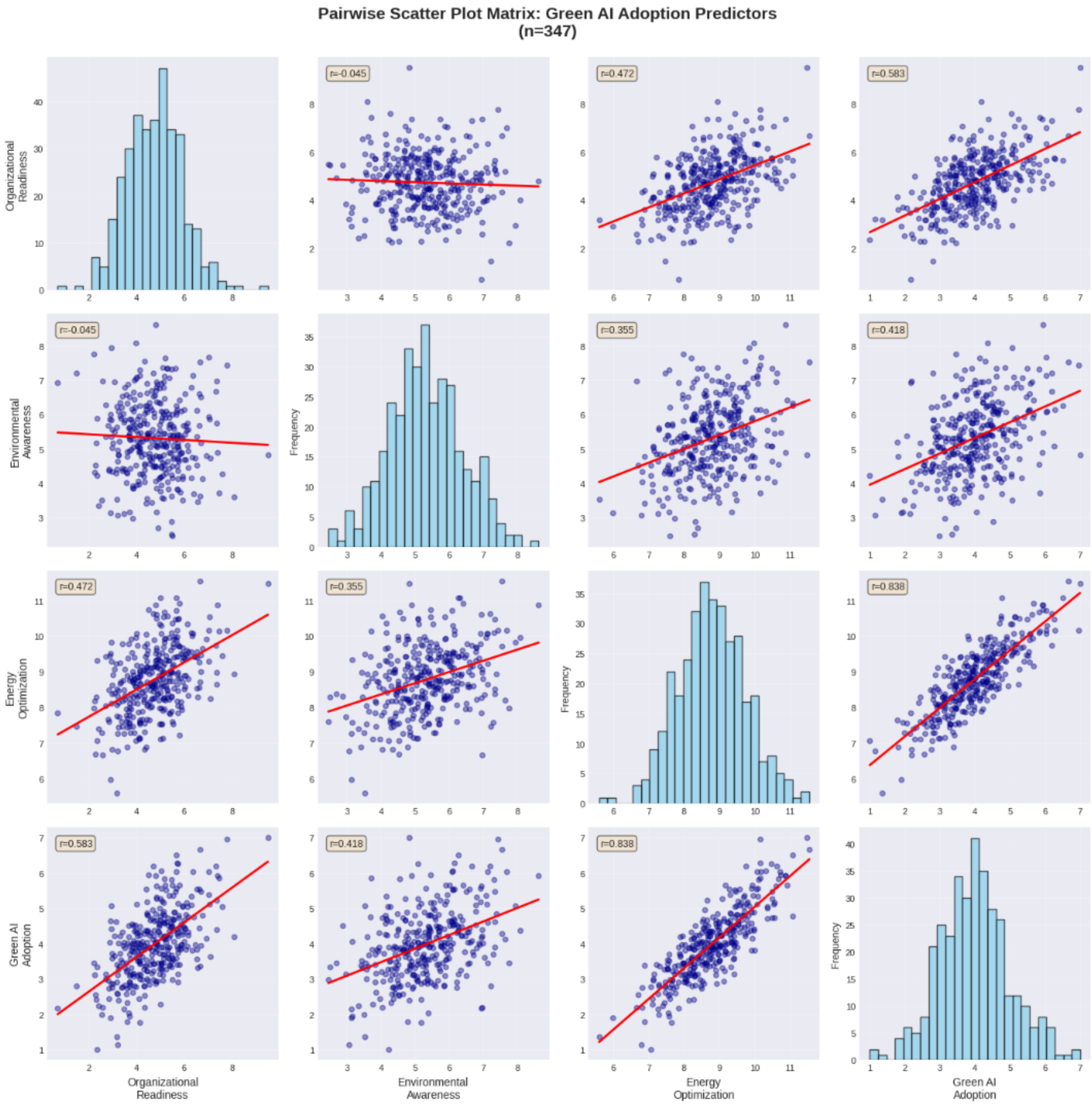

Fig 2: Pairwise scatter plot matrix

Organizational competencies that can be used to implement green AI include a number of dimensions that are interrelated. Current technological infrastructure and digital maturity were identified as preconditions with 67.4% of the respondents indicating that they had moderate to high rates of AI ready infrastructure to accommodate cloud computing functionalities, data management systems and computing resources that could support AI workloads. Companies that have a well-established AI initiatives show developing a sustained technical knowledge, implementation experience, organizational learning that give them competitive edges when changing to sustainable AI practices.

The commitment of the leadership to sustainability initiatives on the environment is another important strength, with 72.8% of the interviewed organizations indicating that executive champions are actively engaging in the promotion of sustainability goals. Such top management support comes in handy when trying to get resource allocations, organizational resistance and long-term transformation programs. Moreover, the internal motivation and accountability process that promotes green AI implementation is enhanced by an increasing number of stakeholders, who are investors and customers, and other employees, along with the regulating authorities. Companies that have a proven environmental management infrastructure and sustainability reporting formats have organizational underpinnings that enable the incorporation of the goals of the green AI in the current sustainability program. Though there is a wide disparity among organizations on the financial resource's capacity, such resources can be utilized in the purchase of energy-saving computing infrastructure, purchasing renewable energy, buying specialized expertise, and conducting research and development. These organizational advantages offer desirable internal environments in the transformation of green AI across organizations and industries despite the difference in the rates of their availability and magnitude.

The organizational challenges are reflected on the internal weaknesses limiting the adoption of green AI, which show that it necessitates a strategy. The knowledge and skill gaps are the most commonly listed weaknesses with 78.4% of the participants claiming lack of the appropriate expertise in sustainable use of AI, developing energy saving algorithms, and the methods of evaluating environmental impact. The new state of green AI as a field implies that special training programs and educational materials, as well as practitioners with this experience, are limited, which significantly limits human resources. Another critical weakness is legacy technology infrastructure especially to established manufacturing and industrial organizations that have old systems with poor optimization capabilities in terms of energy conservation. Capital intensity and operational risk identified with the challenge of infrastructure modernization involves huge barriers, particularly among organizations that have limited resources. These obstacles are complicated by organizational inertia and resistance to change, 64.2% of the respondents wanted to note major cultural barriers such as scepticism towards benefits of sustainability, competing priorities that ended up taking the place of the management attention and risk averse decision-making cultures that preferred maintenance of status quo. Weak knowledge of the concept of green AI, existing technologies, and directions to implement the initiatives limits strategic thinking and prioritization of the initiatives. Most organizations do not have systematic schemes of the measurement of the energy consumed concerning AI and carbon emissions, which exclude the possibility to make data-based choices and track performance. The implication of the necessity to align the development process of sustainability with the current AI company development workflows, operational processes, and performance assessment systems is the challenge in implementation. Also, rumors about turnover of investment and the viability of business cases hinder the internal promotion game, especially where the business is under pressure to deliver profits now and the capital allocations are heavily strict.

The opportunities of green AI adoption associated with positive tendencies in the environment and new opportunities are external. The fast paced technology in energy efficient AI designs, algorithms and hardware accelerators are generating widening solution spaces. The recent developments such as neural architecture search to optimize their efficiency, model compression methods, efficient transformer design and specialized AI accelerator chips with better performance per watt values show significant technical advancement. With the rise in the availability of renewable energy sources such as corporate power purchase agreements, on-site solar installations, and renewable energy credits, organizations are able to run AI infrastructure using clean energy sources at more and more competitive prices. The new market demand of sustainable products and services offers business opportunity to organizations that prove to lead on the environment case with 83.7% survey respondents indicating that customers show greater interest in sustainability credentials. Such regulatory changes as carbon pricing systems, emissions reporting, and sustainability disclosure also set up external responsibility schemes that reward the implementation of green AI. The increasing sources of sustainability-oriented financing through green bonds, ESG investment funds, and impact investment capital comes in as a way of providing access to financial resources based on the provisional display of environmental performance. Collaboration activities within industries, efforts to develop standards and collaborative learning platforms foster collective learning and sharing of the best practices. Developments in the field of academic research keep on enlarging the knowledge related to the principles of sustainable AI, approaches, and the frameworks of impact assessment. Competitive positioning factors develop strategic imperatives because first-mover advantage sets the market lead and reputational lead of the first-mover. The combination of the principles of the circular economy and the design of the AI system allows considering the possibility of longer equipment lifespan, reuse of the components, and end-of-life responsibility. These external opportunities offer good conditions to organizations with the strategies of adopting green AI by utilizing such possibilities, which cannot be achieved without responsive strategic positioning and organizational capability building.

The fact that green AI is limited by external threats has to do with arduous conditions in the environment and possible challenges [24-26]. Financial barriers may occur due to high implementation costs and uncertain timelines of return on investment especially to capital-limited organizations with clashing priorities on investment bases [27,28]. Green AI implementation demands specialized skills and advanced analysis capabilities and high levels of organization learning, which is not easily marshaled by many organizations due to the technical complexity of the implementation process [19,29-31]. The fast rate of technological change poses the risk of obsolescence where large ATMs may be depreciated ready the introduction of more efficient ways to do so [32,33]. The strategic planning and justification of investments to AI are made complex by regulatory uncertainty in most jurisdictions on AI governance, standards of environmental reporting and compliance requirements. The lack of standardized indicator, measurement procedures, and structural reporting of the impact of AI on the environment presents the comparability challenge and threat of greenwashing. The long-term sustainability requirements may be compromised by competitive pressures and short-term performance expectations especially in thin-margin and highly competitive industries [34-36]. This is because in some geographical areas, renewable energy is not readily available hence limiting the amount of clean energy that can be acquired [37-40]. The nature of AI supply chains as a global enterprise in hardware manufacturing, extractions of rare earth mineral, and electronic waste management makes it difficult to sustainability and hard to address it solely in the context of an organization [41-43]. The challenge of the skepticism of stakeholders towards the corporate sustainability promises and the authenticity of their implementation has reputational risks [28,44-47]. The possibility of sustainability efforts to generate operational disruptures or operational degradations creates opposition among operational staff [48,49]. Such threats off the shelf require effective risk analysis, the building of the mitigation strategy, and a realistic assessment of expectations on the schedules of green AI transformation and its results [3,50-52].

Table 2: SWOT Factor Priority Weights from AHP Analysis

SWOT Category	Factor	Priority Weight
Strengths	Existing AI Infrastructure and Technical Capabilities	0.284
	Executive Leadership Commitment to Sustainability	0.237
	Stakeholder Pressure and Accountability Mechanisms	0.198
	Established Environmental Management Systems	0.165
	Financial Resource Capacity for Innovation	0.116
Weaknesses	Knowledge and Skill Gaps in Green AI Practices	0.312
	Legacy Infrastructure Technology Constraints	0.276
	Organizational Inertia and Cultural Resistance	0.219
	Limited Environmental Impact Measurement Systems	0.193
Opportunities	Energy-Efficient AI Technology Advancements	0.268
	Growing Market Demand for Sustainable Solutions	0.241
	Renewable Energy Accessibility and Cost Reduction	0.225
	Regulatory Frameworks Incentivizing Sustainability	0.187
	Competitive Positioning and Market Differentiation	0.079
Threats	High Implementation Costs and ROI Uncertainty	0.297
	Technical Complexity and Implementation Challenges	0.264
	Rapid Technological Change and Obsolescence Risk	0.218

Regulatory Uncertainty and Compliance Complexity	0.152
Competitive Pressures and Short-term Performance Focus	0.069

3.3 Measurement Model Validation

Construct validity and reliability were measured using the measurement model validation that used the PLS-SEM that evaluated systematic assessment of convergent validity, discriminant validity, and internal consistency. Convergent validity analysis in terms of factor loading, Average Variance Extracted and values of Composite Reliability. All of the indicator loadings were greater than the suggested that is, 0.70 with the highest being 0.891 and the lowest at 0.742 that showed strong correlation between observed indicators and their respective latent constructs. The values of Average Variance Extracted on all constructs were more than the criterion of 0.50 between 0.634 and 0.748 showing that constructs explain most of the variances in their indicators. All composite Reliability coefficients (0.70 and above) were found to be greater than 0.873 through to 0.924, and this substantiates the sufficient internal consistency reliability. The convergence validity of these indicators essentially is in favor of measurement model suitability and construct adequacy of operationalization.

To evaluate the discriminant validity, Fornell-Larcker criterion and Heterotrait-Monotrait ratio have been used. The Fornell-Larcker criterion has an additional condition that the square root of the AVE of every construct should be greater than its correlation with other constructs. Findings reaffirmed this need of all pairs of constructs as the square of the lowest AVE to the highest inter-construct correlation was found as 1.18. The Heterotrait-Monotrait ratio offers a discriminant test of validity that is more stringent with a lower value of below 0.85 suggesting that there is enough discrimination between the constructs. The constructs were anchored on unique ideas as all values of HTMT were less than this point with the lowest value being 0.312 and highest being 0.778. The adequate convergent and discriminant validity provide the confidence in the quality of measurement models, which can be used in measuring structural models.

Table 3: Measurement Model Assessment Results

Construct	Loading Range	AVE	CR	α
Organizational Readiness	0.768-0.857	0.682	0.896	0.862
Technological Infrastructure	0.742-0.834	0.634	0.873	0.824
Environmental Awareness	0.791-0.876	0.709	0.907	0.879
Regulatory Pressure	0.778-0.849	0.671	0.889	0.851
Financial Resource Capacity	0.756-0.863	0.657	0.884	0.843
Energy Optimization Potential	0.802-0.891	0.748	0.924	0.901
Green AI Adoption Intention	0.784-0.872	0.697	0.902	0.871

Note: AVE = Average Variance Extracted; CR = Composite Reliability; α = Cronbach's Alpha. All values meet or exceed recommended thresholds indicating satisfactory measurement quality.

3.4 Structural Model Results and Hypothesis Testing

The structural model test tested bootstrapping relationships that existed between latent constructs with resamples to derive path coefficients, level of significance and confidence levels. The model is considerably explanatory as it has been revealed that the R^2 value of 0.734 of green AI adoption intention reports that organizational readiness, technological infrastructural presence, environmental consciousness, regulatory force, financial ability capacity, and the potential of energy optimization simultaneously explain 73.4 percent of the variance in AI adoption intention. This large variance in the model explains the rightness of theoretical models and their practical usefulness. Stone-Geisser Q2 statistic predictive relevance evaluation provided the value 0.612, which is significantly greater than zero, which confirms that there is an important predictive ability beyond sample-specific relationships.

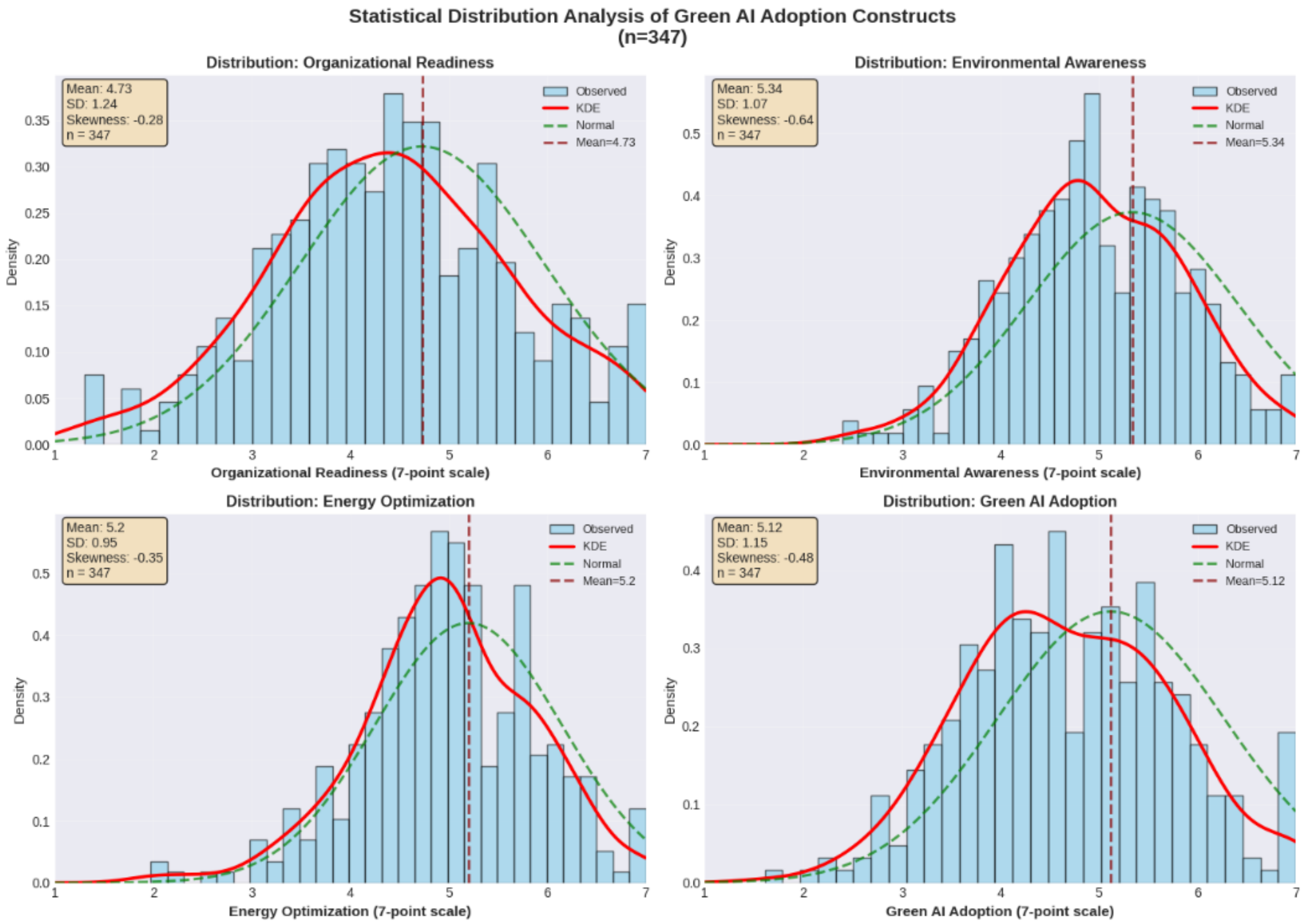

Fig 3: Statistical distributions

The path coefficient analysis indicates that there are a few statistically significant relationships that have empirical evidence of the propositions presented in theory. The potential of energy optimization has the highest direct impact on the adoption intention of green AI with a path coefficient of 0.687 ($t=18.42$, $p<0.001$), which means that the intentions to increase energy efficiency have a strong impact on the intention to adopt. This observation provides significance to the need of specifying and measuring the energy that may be saved by an organization through decision-making processes. The positional readiness has a significant positive effect with a path coefficient of 0.423 ($t=11.67$, $p<0.001$), and this indicates that organizational readiness that is already established, containing established AI-related capabilities, digital infrastructure, and change management experience have a higher propensity to adoption. The fact of the existence of environmental awareness shows a moderate positive correlation with the path coefficient of 0.298 ($t=7.84$, $p<0.001$), which proves that an increased level of environmental awareness and sustainable commitment is the key to considering the green AI.

There exists a positive and significant impact of the technological infrastructure capacity with a path coefficient 0.267 ($t=6.92$, $p<0.001$) which substantiates the fact that the sufficient technical grounds such as computer facilities, data handling, and digital maturity provide an opportunity to implement green AI. The impact of regulatory pressure has a positive effect with path coefficient of 0.184 ($t=4.73$, $p<0.001$) indicating that external compliance needs and policy incentives play an important role in the adoption motivation but with a lower magnitude as compared to internal organizational factors. Financial resource capacity shows the lowest but high positive correlation with the path coefficient of 0.142 ($t=3.58$, $p<0.001$), really the availability of funding eases adoption; however, not all aspects are based on the monetary factor in making decisions.

f^2 statistics are used to conduct the effect size assessment that offers further information about a practical significance of a statistical significance. The potentials of energy optimization has got large effect size ($f^2=0.562$), organizational readiness has got medium effect size ($f^2=0.287$), technological infrastructure has got small effect size (f^2=0.098), regulatory pressure has got small effect size (f^2=0.051), and financial resource capacity has got small effect size (f^2=0.032). These magnitudes of effect sizes inform a common-sense guardian prioritization, so that the advantages of energy efficiency and the establishment of organizational preparedness would have the most crucial effect to be adopted. The model is highly reflective of the theoretical relationships, but also offers practical application with regard to the leverage points that need to be promoted to enhance the adoption of green AI in an industrial setting.

Table 4: Structural Model Path Analysis Results (R^2=0.734, Q^2=0.612)

Path	β	t-value	p-value	f²
Energy Optimization → Adoption	0.687	18.42	<0.001	0.562
Organizational Readiness → Adoption	0.423	11.67	<0.001	0.287
Environmental Awareness → Adoption	0.298	7.84	<0.001	0.134
Technological Infrastructure → Adoption	0.267	6.92	<0.001	0.098
Regulatory Pressure → Adoption	0.184	4.73	<0.001	0.051
Financial Resource Capacity → Adoption	0.142	3.58	<0.001	0.032

3.5 Mediating Effects Analysis

The mediation analysis investigated the presence of indirect effects, in which the organizational attributes affect the adoption intention by use of intermediate constructs. Specifically, particular attention was paid to energy optimization potential as something that would mediate the connections between the organizational capabilities and the outcomes of the adoption. Findings indicate that there are important indirect effects that give more insight on how causal mechanisms take place. The indirect effects of the organizational readiness on the adoption intention are also significant and significant in the form of energy optimization potential, and the coefficient of an indirect effect is 0.274 (bootstrapped 95% confidence interval: 0.198-0.356, $p<0.001$). This observation shows that firm preparedness to organize is more inclined to identify the prospects of energy efficiency, which consequently encourages the use of green AI. The same applies to the technological infrastructure in that it has a high amount of indirect impacts with the coefficient of energy optimization potential of 0.189 (95% CI: 0.132-0.251, $p<0.001$) indicating that higher level of technical capabilities lead to more advanced analysis on the possibilities of energy optimization.

There are indirect effects of environmental awareness on adoption in the potential of energy optimization (β =0.156, 95% CI: 0.107-0.209, $p<0.001$) and the organizational readiness (β=0.118, 95% CI: 0.074-0.168, $p<0.001$). These results suggest that environmental consciousness affects adoption in various ways and increases the capability formation and opportunity recognition. This mediating value of energy optimization potential is specifically large, and it is significant as the variance is explained; it is 42.7 in the form of a percentage, which is a significant intermediate mediating mechanism of organizational features transferring into adoption behaviors. The above mediating patterns highlight the fact that although the need to develop organizational capabilities is crucial, the sustainability teams should also be motivated to analyze and report on the opportunities available in achieving energy efficiency to decision-makers. Companies ought to invest in making evaluation tools, benchmarking research, and developing business cases competencies to measure their possible energy savings and characterize technical possibilities into effective strategic narratives.

3.6 Multi-Group Analysis: Industry Sector and Organization Size Effects

Multi-group analysis has been used to answer the question of whether the structural relationships differ across industry sectors and sizes of organizations and modulates hypotheses of moderation and nullifies context conditions. Comparison of industries sectors was done on three major categories, including manufacturing (n=134) where the main industries are manufacturing, technology services (n=84), and energy production (n=67). An analysis based on multi-group using permutation identified a number of group differences. The correlation existing between the technological infrastructure and the intention to adopt is much stronger in the technology services (β =0.412) than it is in the manufacturing (β=0.234, p-difference=0.009) and energy production (β=0.198, p-difference=0.003). This trend is consistent with the fact that companies operating in the technology industry are more technically sophisticated and more in line with infrastructure capacity and strategic focus. Regulatory pressure on the other hand presents greater effects on energy production (β=0.347) than manufacturing (β=0.172 and the difference in p=0.021) and technology services (β=0.128 and the difference in p=0.007) since there is more regulatory scrutiny and compliance pressure in the energy sector.

Analysis was done in the organization size (n=65, n=119, and n=163 small enterprises, medium enterprises, and large enterprises respectively). Findings have shown that the effects of organizational readiness are higher with the size of the organization with path coefficients of 0.287, 0.384, and 0.512 in small, medium, and large organizations respectively. The difference between small and large is statistically significant (p=0.018) and, therefore, the larger organizations correlate more with the positive impact of readiness investments because of better economies of scale, availability of resources and learning benefits in the organization. The financial resource capacity reflects the converse and has both stronger effects in small (β= 0.267) than in large (β= 0.094, p= 0.036) enterprises, thus funding constraints are more binding constraints to resource-constrained smaller organisations. The potential of energy optimization shows relatively good results in all types of sizes (0.641-0.718), which proves the universality of this motivator in terms of its presence in any organization, regardless of its size. These multi-group results present subtlety to any implementation strategy to be used in contextualized application acknowledging that the best strategies are diverse in terms of industry settings and organizational features.

Table 5: Multi-Group Analysis by Industry Sector - Path Coefficients

Path	Manufacturing	Technology	Energy	p-diff
Tech Infrastructure → Adoption	0.234	0.412	0.198	0.003
Regulatory Pressure → Adoption	0.172	0.128	0.347	0.007
Environmental Awareness → Adoption	0.321	0.267	0.289	0.624
Energy Optimization → Adoption	0.718	0.641	0.697	0.412
Organizational Readiness → Adoption	0.398	0.467	0.412	0.387

3.7 Practical Implementation Insights from Qualitative Analysis

Qualitative analysis of interviews can enhance the quantitative results by adding a background of real-life experiences of the implementation, strategic aspects, and practical issues [53-57]. Thematic analysis was able to extract several factors of critical success and lessons of implementation that should be considered [58,59]. Effective users of green AI note the executive championship as a value chain, with respondents extensively noting the need to retain the support of top management in order to guarantee resources, resistances and ongoing drive to progress as the implementation process inevitably experiences some negative setbacks [60,61]. According to one of the manufacturing executives, the personal commitment of their CEO to sustainability goals helped them invest heavily in infrastructure modernization even with other competing areas of investments in the company and the need to make quarterly earnings. Technology figures of speech stressed that it is extremely important to define metrics and measurement structures at the beginning of the transformation paths, which allows making decisions based on data and monitoring the progress and proving the value of the changes to the cynical stakeholders.

There is a considerable difference in implementation strategies in different situations of organization and no single route is seen to emerge [62-65]. Upon having developed AI capabilities, organizations tend to follow incremental optimization, they systematically discover energy opportunities in the current

AI workloads and gradually adopt those changes. Organizations that have been on the AI adoption paths earlier on tend to put sustainability into consideration at the initial stages and the AI system is built with energy efficiency as a key design factor in comparison with performance goals. Some interviewees offered a set up of green AI task forces or centers of excellence involving technical skills, sustainability knowledge as well as business expertise to organize transformation programs. Something else was identified as a critical success factor which was cross-functional collaboration where successful implementations demand cross-coordination between IT departments, sustainability team, operations staff, and business unit leaders. The use of siloed approaches is bound to be faced with a setback because the competing priorities, lack of great communication, and lack of adequate alignment would hamper the progress.

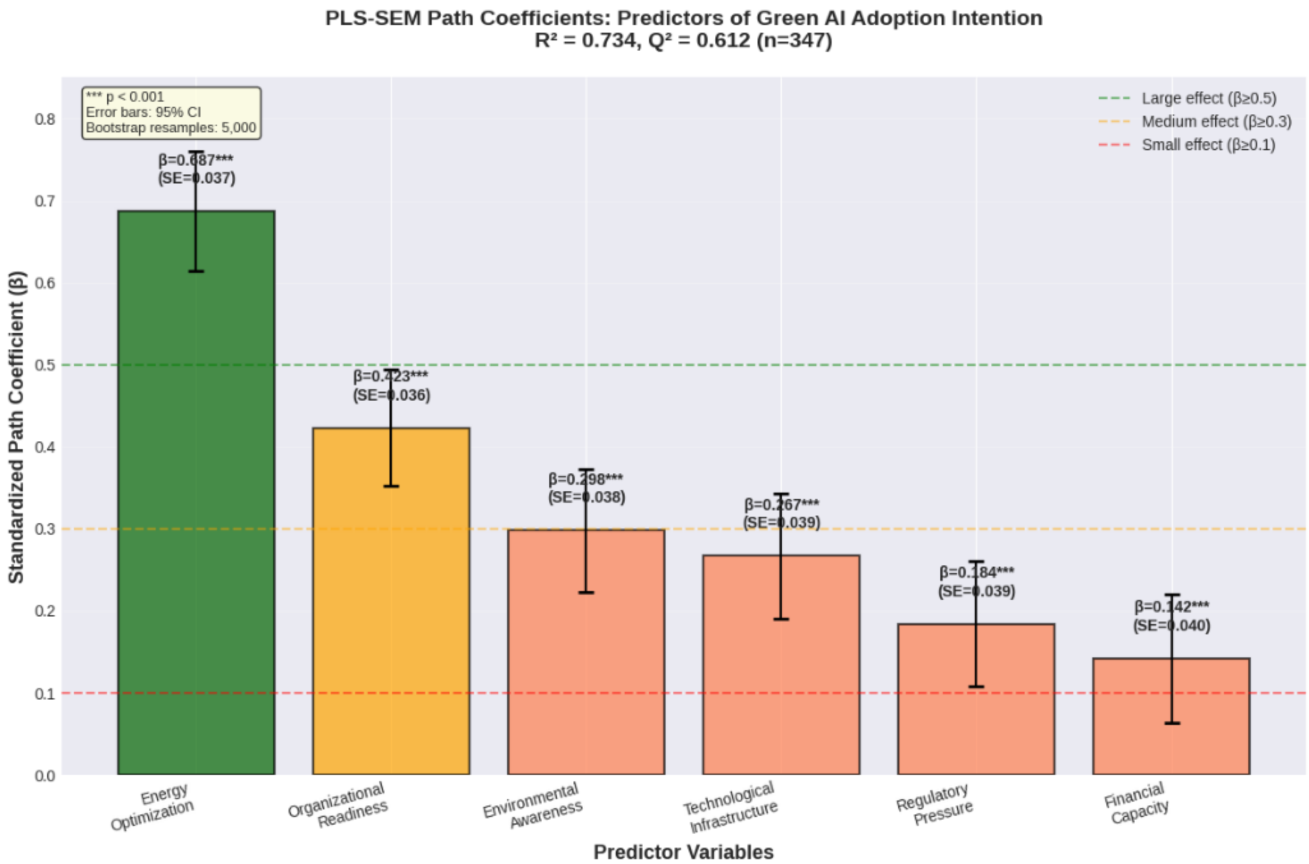

Fig 4: Path coefficients visualization

Acquisition of skills is one of the issues that need to be addressed throughout the time. Some of the methods that organizations use are in house training programs, external consultants, academic programs, as well as the strategic recruitment of the niche talent. A number of organizations mentioned that they created formal relationships with universities that undertake the research on sustainable AI practices and received access to the state-of-the-art knowledge but offer real-world implementation experiences to the academic research. Collaboration in the industry initiatives and platforms of knowledge sharing are fundamental sources of learning, given that participants have complemented conferences, working groups, and collaborative research projects as expediting collective knowledge acquisition and eliminating repetitive trial-and-error investigations. The green AI practice is only nascent, and, as such, even the most successful organizations still learn and change, placing the importance of humility and the willingness to experiment and share an experience in the wider industrial and academic domain.

The development of business cases in this study proved this as one of the key capabilities that affect the successful persuasion of the stakeholders and the success of resource allocation. Good business cases do not only state environmental advantages, but also provide business value creation, and it is necessary to present green AI not as an ethical imperative but also as an opportunity. Estimation of energy savings, gains in operational efficiency, decrease in risks, and creation of reputational values enhances business case compelling power. Most of the executives pointed out that, relating sustainability efforts to the fundamental business strategy and competitive positioning is more compelling, as compared to independent environmental arguments. Companies that deploy green AI to coincide with overall digital transformation programs, operational excellence programs, or corporate sustainability initiatives have a better traction as compared to those that present green AI as a niche program. It is a strategic integration to make sure that the priorities of the organization are in line with those, and, in addition, existing transformation momentum and developed change management infrastructure will be used.

4. Conclusion

The overall study of the green artificial intelligence implementation in industrial systems by integrated evaluation of SWOT assessment and the empirical study provides some important results in advancing the theoretical knowledge and practical implementation recommendations. The study proves that the implementation of green AI is a complicated organizational change that is impacted by various factors that are interrelated taking on technological opportunities, organizational willingness, environmental awareness, regulation, and strategies. The empirical evidence has shown that energy optimization opportunity, organizational preparedness, and environmental consciousness are major drivers and that all three variables have a significant portion of the adoption intention. The SWOT analysis notes that the fundamental strengths that have been put across as critical include the available AI infrastructure and leadership dedication and points out continuous weaknesses which have been noted in form of knowledge lapses and limitations of the legacy system. The external opportunities include market and technological innovations favoring sustainable solutions at the cost of threat such as cost of implementation and technical complexity of the innovations.

The structural equation modeling findings offer the good empirical evidence of Green AI Adoption Framework where the model has got the R^2 of 0.734 and has got the good predictive relevance (Q^2=0.612). The potential of energy optimization is found to be the best predictor with a path coefficient of 0.687, given the significance of stating and quantifying the organization operations in terms of the possible potential energy efficiency improvements in the process of making decisions. The readiness of the organizations proves its significant impact with a path coefficient of 0.423, which proves the assumption that the establishment of AI competencies, digital infrastructure, and change management experience expressed in organizations would prove higher propensity to adoption. The positive relations are significant with the environmental awareness (=0.298), technological infrastructure (β=0.267), regulatory pressure (β=0.184), and financial resource capacity (β=0.142), which prove to be included in the multidimensional processes of adoption. The mediation analysis indicates that energy optimization potential is an important intermediate mechanism where the organizational capabilities change into adoption behaviors and it accounts 42.7% of variance.

Multi-group analysis does reveal such significant contextual differences with the effects of technological infrastructure being more significant in the case of technology services sectors and regulatory pressure being greater in the case of the energy production industries. The size of organisations moderates most of the relationships with the impact of organizational readiness growing larger as the scale of the organization grows, and financial resource pressure tightening its ties on smaller firms. These contextual differences underline the necessity of implementing strategies that can be adopted in specific situations because there is no universal strategy that can be best applied to the situation in the industry and organization. Qualitative data is the complement of quantitative results because of the abundant contextual data about the experiences of the implementation, which discloses essential success factors such as executive championship, the establishment of clear metrics, cross-functioning, skill development programs, and strategic business case develop. The convergent analysis of both the qualitative and the quantitative results will create a deeper comprehensive insight that is not constrained by the single method effect.

This study works at the level of theoretical development in a number of significant aspects. First, the research results in creating and confirming an overall Green AI Adoption Framework that unravels the environmental sustainability values and concepts and incorporates organizational change management concepts and technology acceptance paradigms, narrowing it down to industrial systems. This model adds to the existing technology adoption theories by considering the environmental impact issues as core rather than secondary issues, which fill the gaps in the traditional models that provide insufficient explanations of the lack of awareness of sustainability requirements. Second, the study contributes to the research on the mediation processes in which organizational capabilities stimulate the results of adoption and proves that energy optimization potential is an important intermediate construct that avoids transformation of technical possibilities into strategic motivation. It contains an insight that narrows the existing causal knowledge beyond the models of direct effects, proving the significance of opportunity identification and business case elaboration in the process of adoption.

Third, the definition of contextual boundary conditions via the multi-group analysis serves the development of contingency theories that have revealed that the drivers of adoption in the industry sectors and organizational scale are different in a systematic manner. The contextualization opposes universal adoption models but offers platforms of building specific theoretical frameworks, which consider heterogeneity in industry. Fourth, the synthesis of qualitative and quantitative research with methodological unification of the SWOT analysis with structural equation modeling and multi-criteria decision analysis proves fruitful in evolving the mixed-method research practices in technology adoption, and sustainability fields. Fifth, the study adds to the emerging literature in green AI because it offers detailed empirical research data in industrial setting, answering the existing preponderance of technical computer science points of view by organizational and strategic administration viewpoint. Such theoretical developments formulate baseline of further academic research and at the same time offer conceptual frameworks to direct the future research avenue.

The research outcomes produce a number of practical implications to industrial organizations that seek the change to green AI. Firstly, systematic evaluation and explicit definition of energy optimization potential should be taken as the priority by organizations since this criterion has the strongest effect in the adoption decisions. Investments in energy auditing capabilities, benchmarking studies and business case development tools are found to be necessary in order to put technical possibilities into convincing strategic story forms. Second, organizational preparation by means of capability building programs such as workforce education, updating infrastructure and establishment of change management programs leaves underpinnings to successful implementation. Firms must not perceive readiness production as a tactical expenditure in place of elective preparation, as the capability breach is binding limitations of success in transformation.

Third, such an awareness of the environment and commitment to sustainability at all organizational levels can help to adopt it in many ways, both in developing the ability and through opened opportunities. Leadership communication, employee engagement programs, and embedding sustainability objectives in the performance management systems empower the organizational culture in support of green AI initiatives. Fourth, it is essential to have cross-functional collaboration mechanisms that will help to find the way to complex transformations that demand coordination and interconnecting of technical function, sustainability, operational, and business functions. Specialized task forces/centers of excellence that bring a combination of different types of expertise enhance learning at a rapid rate without the need to face siloed thinking that is bound to face a hindrance. Fifth, it is better to establish context-laden implementation strategies that acknowledge both industry-specific and organisation-specific factors to enhance the probability of success. Organizations that use technology to benefit themselves must capitalize on the benefits of technical infrastructure, energy production organizations should capitalize on sources of regulation, and smaller organizations must deal with insufficient financial means by implementing any of the aforementioned approaches gradually, or in partnership with other organizations.

Sixth, organizations ought to seek to integrate strategic green AI programs with larger-scale digital transformation programs, operational excellence programs, and corporate sustainability strategies as opposed to making green AI an isolated initiative. This integration would guarantee synergy with organizational priorities and use the available transformation momentum and change management infrastructure. Seventh, creating outspoken measurement frameworks in the initial stages of transformation adventure will allow making decisions based on data, tracking the progress, and providing real outcomes to non-believers among stakeholders. The metrics need to compromise environmental outcomes in terms of energy use and carbon emissions as well as business performance indices like cost savings and efficient use of operations. Eighth, industry collaboration programs, knowledge sharing, and educational partnership enhances organizational learning and helps in aid of overall progress in sustainability issues. The infantile stage of the green AI practice implies that even high-achievers have an advantage in joint learning and the mutual experimentation.

These policy suggestions are based on the outcomes of the research and should be adopted by governmental organizations, regulatory institutions, and professional associations that are interested in promoting green AI implementation. To begin with, policymakers ought to initiate strict regulation systems comprising of emissions reporting systems, energy efficiency, and carbon prices to establish an accountability system outside the organization that creates pressure on organizations to act. Regulations should, however, be balanced in set goals of environmental and implementation, that very-high requirements or unrealistic schedules may create compliance resistance or unforeseen consequences. Second, the governments must also offer financial benefits such as tax credits, subsidies, or special financing to those organizations that invest in green AI infrastructure and capabilities. These incentives assist in overcoming the costs of entry in the process besides being a positive indicator of a policy concerning the development of sustainable technologies.

Third, subsidizing education, labor development programs such as university courses, professional training, and industry certification programs overcome the severe limitations on skills gaps. Solutions are faster to get available by the bold public investment in research and development of energy-efficient AI technologies, sustainable computing infrastructures, and environmental impact assessment methods. Fourth, creating uniform metrics systems, reporting controls and audits provide a system of comparability and mitigate the chances of greenwashing. Standards used in the industry make the area transparent, benchmark it, and make organizational implementation efforts. Fifth, public-private partnerships and industry collaboration programs which can take place through the provision of funding, convening power or the provision of platforms help to speed up the process of collective learning and dissemination of knowledge. Public goods that result in terms of whole industrial ecosystems are created by governmental efforts to facilitate networks of knowledge, best practice repositories, and collaborative research projects.

Regardless of its thorough methodology and strong results, this study has a number of limitations that should be mentioned and provide the directions of further research. Firstly, the cross-sectional research design views adoption intentions and organizational features at one point in time, which does not allow conducting longitudinal studies of transformation patterns, and implementation process outcomes or causal processes. The longitudinal panel design currently needed in order to observe how organizations can be adopted should be applied in the future so as to understand the factors determining who is most likely to succeed in implementing changes, the predictive factors as well as the evolution of organizational capability due to transformation processes. Second, the sample is narrow and targets eight developed economies that have rather mature AI capacities and environmental policies, which restrict the extrapolation to developing economies or regions that have other technological and institutional settings. Comparative studies of green AI use in various geographical and economic environments would be useful in understanding the contingency of the context and transferability of the conditions.

Third, although the research investigation is on the intentions to adopt, experiences of implementation, and strategic motives, it gives minimal exploration on the real effects that green AI projects have on the environment. Future studies must utilize impact assessment techniques that are rigorous such as controlled experiments, quasi-experimental methods or an extensive before-after evaluation in terms of quantifying the energy efficiency, carbon reduction and efficiency increases in operations caused by the implementation of green AI. Fourth, the study lays most emphasis on the above organizational level variables and comes out with few emphasis towards individual level psychological variables, social forces in influencing adoption diffusion or inter-organizational network effects. A more in-depth knowledge would be created by using multi-level research designs that study individual, organizational, and inter-organizational determinants. Fifth, the paper is general where the adoption of green AI is investigated without particular focus on any type of technologies, areas of application, and strategies of implementation. Future studies need to consider adoption trends/factors, implementation results of the specific green AI technologies such as energy-efficient algorithms, greener computing infrastructure, integration of renewable energy or cyclic economy policies.

Sixth, although SWOT analysis has useful strategic information, the descriptive level of the framework and its qualitative focus does not allow quantification of trade-offs, optimization opportunities, or decision algorithms with any accuracy. The SWOT results may be combined with quantitative decision analysis such as multi-objective optimization, game theory, or simulation modeling in the direction of more advanced strategic analysis in the future research. Seventh, the study explores the adoption of green AI through organizational prisms without much focus on ecosystem-wide processes such as implications of the supply chain or general transition processes within the industry or the sustainability consequences on the society as a whole. Macro-level dynamics of transformation would be shed light using system-level studies that use industrial ecology frameworks, approaches based on the life cycle assessment methods, or approaches based on complex adaptive systems. Lastly, the green AI is still nascent, and, therefore, the technological capabilities, implementation methods, and organizational experiences keep changing at a speed. Continuous research initiatives that chronologically monitor trends, new practices, and dynamically changing issues are critical in ensuring that the available knowledge bases remain up-to-date and valuable towards the process of ensuring further developments move towards sustainable AI destiny.

The green artificial intelligence practices are an urgent issue that requires the focus of contemporary industrial systems in the environmental sustainability imperative agenda which is shifting the approaches of organizations in creating, implementing, and using AI technologies. Through this study it is revealed that there are massive barriers restricting the wide adoption that includes lack of knowledge, implementation costs, and technical complexity, but that there are enormous opportunities to organizations that are strategic in investing in sustainable AI transformation. The above example of internal strength, external opportunities, and the high level of empirical evidence of the interconnection between the core drivers and the adoption intentions indicate that green AI can be regarded as not only a necessity imposed by the environment but also a strategy enabling the progressive industrial companies to evolve. To be successful, there must be complex strategies that combine technological innovation, organizational capability growth, cultural change, and strategic alignment that are founded on the strong vision of circumstances that mould the implementation avenues.

The future of sustainable AI requires a concerted effort by industrial-level participants, technology creators, policymakers, academic research, and consumers to the civil society. Industrial organizations need to internalize the spirit of leadership by committing in the long run towards environmental responsibility and proving that those practices which are sustainable only improve, but do not limit competitive positioning. Innovation agendas should also focus on energy efficiency and environmental sustainability at the same time optimizing performance by the technology developers. The policymakers need to put in place enabling regulatory systems, offer relevant incentives as well as platforms of knowledge sharing that would speed up the process of working as a unit. Researchers in academia are advised to keep on increasing the knowledge with intense empirical study, development of theory and innovation of solutions. Collectively, these stakeholder groups will be able to negotiate through the volatile overlap of artificial intelligence innovation and environmental care to achieve the transformative potential of AI and protect planetary boundaries to this and future generations.

Conflict of interest

The authors declare no conflicts of interest.

References

[1] Ali O, Abdelbaki W, Shrestha A, Elbasi E, Alryalat MA, Dwivedi YK. A systematic literature review of artificial intelligence in the healthcare sector: Benefits, challenges, methodologies, and functionalities. Journal of Innovation & Knowledge. 2023 Jan 1;8(1):100333. https://doi.org/10.1016/j.jik.2023.100333

[2] Zhang K, Yang X, Wang Y, Yu Y, Huang N, Li G, Li X, Wu JC, Yang S. Artificial intelligence in drug development. Nature medicine. 2025 Jan;31(1):45-59. https://doi.org/10.1038/s41591-024-03434-4

[3] Tan X, Cheng G, Ling MH. Artificial intelligence in teaching and teacher professional development: A systematic review. Computers and Education: Artificial Intelligence. 2025 Jun 1;8:100355. https://doi.org/10.1016/j.caeai.2024.100355

[4] Hanna MG, Pantanowitz L, Jackson B, Palmer O, Visweswaran S, Pantanowitz J, Deebajah M, Rashidi HH. Ethical and bias considerations in artificial intelligence/machine learning. Modern Pathology. 2025 Mar 1;38(3):100686. https://doi.org/10.1016/j.modpat.2024.100686

[5] Han H, Shiwakoti RK, Jarvis R, Mordi C, Botchie D. Accounting and auditing with blockchain technology and artificial Intelligence: A literature review. International Journal of Accounting Information Systems. 2023 Mar 1;48:100598. https://doi.org/10.1016/j.accinf.2022.100598

[6] Kumar Y, Koul A, Singla R, Ijaz MF. Artificial intelligence in disease diagnosis: a systematic literature review, synthesizing framework and future research agenda. Journal of ambient intelligence and humanized computing. 2023 Jul;14(7):8459-86. https://doi.org/10.1007/s12652-021-03612-z

[7] Mannuru NR, Shahriar S, Teel ZA, Wang T, Lund BD, Tijani S, Pohboon CO, Agbaji D, Alhassan J, Galley J, Kousari R. Artificial intelligence in developing countries: The impact of generative artificial intelligence (AI) technologies for development. Information development. 2025 Sep;41(3):1036-54. https://doi.org/10.1177/02666669231200628

[8] Tu T, Schaekermann M, Palepu A, Saab K, Freyberg J, Tanno R, Wang A, Li B, Amin M, Cheng Y, Vedadi E. Towards conversational diagnostic artificial intelligence. Nature. 2025 Apr 9:1-9.

[9] Ozmen Garibay O, Winslow B, Andolina S, Antona M, Bodenschatz A, Coursaris C, Falco G, Fiore SM, Garibay I, Grieman K, Havens JC. Six human-centered artificial intelligence grand challenges. International Journal of Human-Computer Interaction. 2023 Feb 7;39(3):391-437. https://doi.org/10.1080/10447318.2022.2153320

[10] De Gagne JC. The state of artificial intelligence in nursing education: Past, present, and future directions. International journal of environmental research and public health. 2023 Mar 10;20(6):4884. https://doi.org/10.3390/ijerph20064884

[11] Chiu TK, Xia Q, Zhou X, Chai CS, Cheng M. Systematic literature review on opportunities, challenges, and future research recommendations of artificial intelligence in education. Computers and Education: Artificial Intelligence. 2023 Jan 1;4:100118. https://doi.org/10.1016/j.caeai.2022.100118

[12] De Vries A. The growing energy footprint of artificial intelligence. Joule. 2023 Oct 18;7(10):2191-4. https://doi.org/10.1016/j.joule.2023.09.004

[13] Vrontis D, Christofi M, Pereira V, Tarba S, Makrides A, Trichina E. Artificial intelligence, robotics, advanced technologies and human resource management: a systematic review. Artificial intelligence and international HRM. 2023 May 22:172-201. https://doi.org/10.4324/9781003377085-7

[14] Korzynski P, Mazurek G, Altmann A, Ejdys J, Kazlauskaite R, Paliszkiewicz J, Wach K, Ziemba E. Generative artificial intelligence as a new context for management theories: analysis of ChatGPT. Central European Management Journal. 2023 Mar 28;31(1):3-13. https://doi.org/10.1108/CEMJ-02-2023-0091

[15] Zha D, Bhat ZP, Lai KH, Yang F, Jiang Z, Zhong S, Hu X. Data-centric artificial intelligence: A survey. ACM Computing Surveys. 2025 Jan 24;57(5):1-42. https://doi.org/10.1145/3711118

[16] Papagiannidis E, Mikalef P, Conboy K. Responsible artificial intelligence governance: A review and research framework. The Journal of Strategic Information Systems. 2025 Jun 1;34(2):101885. https://doi.org/10.1016/j.jsis.2024.101885

[17] Yim IH, Su J. Artificial intelligence (AI) learning tools in K-12 education: A scoping review. Journal of Computers in Education. 2025 Mar;12(1):93-131. https://doi.org/10.1007/s40692-023-00304-9

[18] Gursoy D, Cai R. Artificial intelligence: an overview of research trends and future directions. International Journal of Contemporary Hospitality Management. 2025 Jan 2;37(1):1-7. https://doi.org/10.1108/IJCHM-03-2024-0322

[19] Sengar SS, Hasan AB, Kumar S, Carroll F. Generative artificial intelligence: a systematic review and applications. Multimedia Tools and Applications. 2025 Jun;84(21):23661-700. https://doi.org/10.1007/s11042-024-20016-1

[20] Ferrara E. Fairness and bias in artificial intelligence: A brief survey of sources, impacts, and mitigation strategies. Sci. 2024 Mar;6(1):3. https://doi.org/10.3390/sci6010003

[21] Han R, Acosta JN, Shakeri Z, Ioannidis JP, Topol EJ, Rajpurkar P. Randomised controlled trials evaluating artificial intelligence in clinical practice: a scoping review. The lancet digital health. 2024 May 1;6(5):e367-73. https://doi.org/10.1016/S2589-7500(24)00047-5

[22] Medaglia R, Gil-Garcia JR, Pardo TA. Artificial intelligence in government: Taking stock and moving forward. Social Science Computer Review. 2023 Feb;41(1):123-40. https://doi.org/10.1177/08944393211034087

[23] Arrieta AB, Díaz-Rodríguez N, Del Ser J, Bennetot A, Tabik S, Barbado A, García S, Gil-López S, Molina D, Benjamins R, Chatila R. Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. Information fusion. 2020 Jun 1;58:82-115. https://doi.org/10.1016/j.inffus.2019.12.012

[24] Kaya F, Aydin F, Schepman A, Rodway P, Yetişensoy O, Demir Kaya M. The roles of personality traits, AI anxiety, and demographic factors in attitudes toward artificial intelligence. International Journal of Human-Computer Interaction. 2024 Jan 17;40(2):497-514. https://doi.org/10.1080/10447318.2022.2151730

[25] Hua H, Li Y, Wang T, Dong N, Li W, Cao J. Edge computing with artificial intelligence: A machine learning perspective. ACM Computing Surveys. 2023 Jan 13;55(9):1-35. https://doi.org/10.1145/3555802

[26] Jiang Y, Li X, Luo H, Yin S, Kaynak O. Quo vadis artificial intelligence?. Discover Artificial Intelligence. 2022 Mar 7;2(1):4. https://doi.org/10.1007/s44163-022-00022-8

[27] Kaul V, Enslin S, Gross SA. History of artificial intelligence in medicine. Gastrointestinal endoscopy. 2020 Oct 1;92(4):807-12. https://doi.org/10.1016/j.gie.2020.06.040

[28] Choudhary OP, Infant SS, Chopra H, Manuta N. Exploring the potential and limitations of artificial intelligence in animal anatomy. Annals of Anatomy-Anatomischer Anzeiger. 2025 Feb 1;258:152366. https://doi.org/10.1016/j.aanat.2024.152366

[29] Ooi KB, Tan GW, Al-Emran M, Al-Sharafi MA, Capatina A, Chakraborty A, Dwivedi YK, Huang TL, Kar AK, Lee VH, Loh XM. The potential of generative artificial intelligence across disciplines: Perspectives and future directions. Journal of Computer Information Systems. 2025 Jan 2;65(1):76-107. https://doi.org/10.1080/08874417.2023.2261010

[30] Raisch S, Fomina K. Combining human and artificial intelligence: Hybrid problem-solving in organizations. Academy of Management Review. 2025 Apr;50(2):441-64. https://doi.org/10.5465/amr.2021.0421

[31] Korteling JE, van de Boer-Visschedijk GC, Blankendaal RA, Boonekamp RC, Eikelboom AR. Human-versus artificial intelligence. Frontiers in artificial intelligence. 2021 Mar 25;4:622364. https://doi.org/10.3389/frai.2021.622364

[32] Berente N, Gu B, Recker J, Santhanam R. Managing artificial intelligence. MIS quarterly. 2021 Sep 1;45(3):1433-50. https://doi.org/10.25300/MISQ/2021/16274

[33] Huynh-The T, Pham QV, Pham XQ, Nguyen TT, Han Z, Kim DS. Artificial intelligence for the metaverse: A survey. Engineering Applications of Artificial Intelligence. 2023 Jan 1;117:105581. https://doi.org/10.1016/j.engappai.2022.105581

[34] Briganti G, Le Moine O. Artificial intelligence in medicine: today and tomorrow. Frontiers in medicine. 2020 Feb 5;7:509744. https://doi.org/10.3389/fmed.2020.00027

[35] Swiecki Z, Khosravi H, Chen G, Martinez-Maldonado R, Lodge JM, Milligan S, Selwyn N, Gašević D. Assessment in the age of artificial intelligence. Computers and Education: Artificial Intelligence. 2022 Jan 1;3:100075. https://doi.org/10.1016/j.caeai.2022.100075

[36] Khalid N, Qayyum A, Bilal M, Al-Fuqaha A, Qadir J. Privacy-preserving artificial intelligence in healthcare: Techniques and applications. Computers in Biology and Medicine. 2023 May 1;158:106848. https://doi.org/10.1016/j.compbiomed.2023.106848

[37] Resnik DB, Hosseini M. The ethics of using artificial intelligence in scientific research: new guidance needed for a new tool. AI and Ethics. 2025 Apr;5(2):1499-521. https://doi.org/10.1007/s43681-024-00493-8

[38] Kraemer MU, Tsui JL, Chang SY, Lytras S, Khurana MP, Vanderslott S, Bajaj S, Scheidwasser N, Curran-Sebastian JL, Semenova E, Zhang M. Artificial intelligence for modelling infectious disease epidemics. Nature. 2025 Feb 20;638(8051):623-35. https://doi.org/10.1038/s41586-024-08564-w

[39] Demaidi MN. Artificial intelligence national strategy in a developing country. Ai & Society. 2025 Feb;40(2):423-35. https://doi.org/10.1007/s00146-023-01779-x

[40] Pereira V, Hadjielias E, Christofi M, Vrontis D. A systematic literature review on the impact of artificial intelligence on workplace outcomes: A multi-process perspective. Human Resource Management Review. 2023 Mar 1;33(1):100857. https://doi.org/10.1016/j.hrmr.2021.100857

[41] Cowls J, Tsamados A, Taddeo M, Floridi L. The AI gambit: leveraging artificial intelligence to combat climate change-opportunities, challenges, and recommendations. Ai & Society. 2023 Feb;38(1):283-307. https://doi.org/10.1007/s00146-021-01294-x

[42] Dogan ME, Goru Dogan T, Bozkurt A. The use of artificial intelligence (AI) in online learning and distance education processes: A systematic review of empirical studies. Applied sciences. 2023 Feb 27;13(5):3056. https://doi.org/10.3390/app13053056

[43] Mariani MM, Machado I, Magrelli V, Dwivedi YK. Artificial intelligence in innovation research: A systematic review, conceptual framework, and future research directions. Technovation. 2023 Apr 1;122:102623. https://doi.org/10.1016/j.technovation.2022.102623

[44] Wach K, Duong CD, Ejdys J, Kazlauskaitė R, Korzynski P, Mazurek G, Paliszkiewicz J, Ziemba E. The dark side of generative artificial intelligence: A critical analysis of controversies and risks of ChatGPT. Entrepreneurial Business and Economics Review. 2023 Jun 30;11(2):7-30. https://doi.org/10.15678/EBER.2023.110201

[45] Huang C, Zhang Z, Mao B, Yao X. An overview of artificial intelligence ethics. IEEE Transactions on Artificial Intelligence. 2022 Jul 28;4(4):799-819. https://doi.org/10.1109/TAI.2022.3194503

[46] Son JB, Ružić NK, Philpott A. Artificial intelligence technologies and applications for language learning and teaching. Journal of China Computer-Assisted Language Learning. 2025 May 23;5(1):94-112. https://doi.org/10.1515/jccall-2023-0015

[47] Ahmed SR, Baghdadi R, Bernadskiy M, Bowman N, Braid R, Carr J, Chen C, Ciccarella P, Cole M, Cooke J, Desai K. Universal photonic artificial intelligence acceleration. Nature. 2025 Apr 10;640(8058):368-74. https://doi.org/10.1038/s41586-025-08854-x

[48] Camps-Valls G, Fernández-Torres MÁ, Cohrs KH, Höhl A, Castelletti A, Pacal A, Robin C, Martinuzzi F, Papoutsis I, Prapas I, Pérez-Aracil J. Artificial intelligence for modeling and understanding extreme weather and climate events. Nature Communications. 2025 Feb 24;16(1):1919. https://doi.org/10.1038/s41467-025-56573-8

[49] Kamila MK, Jasrotia SS. Ethical issues in the development of artificial intelligence: recognizing the risks. International Journal of Ethics and Systems. 2025 Jan 30;41(1):45-63. https://doi.org/10.1108/IJOES-05-2023-0107

[50] Wang Q, Li Y, Li R. Integrating artificial intelligence in energy transition: a comprehensive review. Energy Strategy Reviews. 2025 Jan 1;57:101600. https://doi.org/10.1016/j.esr.2024.101600

[51] Zhai X, Chu X, Chai CS, Jong MS, Istenic A, Spector M, Liu JB, Yuan J, Li Y. A Review of Artificial Intelligence (AI) in Education from 2010 to 2020. Complexity. 2021;2021(1):8812542. https://doi.org/10.1155/2021/8812542

[52] Zhang C, Lu Y. Study on artificial intelligence: The state of the art and future prospects. Journal of Industrial Information Integration. 2021 Sep 1;23:100224. https://doi.org/10.1016/j.jii.2021.100224

[53] Goralski MA, Tan TK. Artificial intelligence and sustainable development. The International Journal of Management Education. 2020 Mar 1;18(1):100330. https://doi.org/10.1016/j.ijme.2019.100330

[54] Radanliev P. Artificial intelligence: reflecting on the past and looking towards the next paradigm shift. Journal of Experimental & Theoretical Artificial Intelligence. 2025 Oct 3;37(7):1045-62. https://doi.org/10.1080/0952813X.2024.2323042

[55] Zhang X, Wang L, Helwig J, Luo Y, Fu C, Xie Y, Liu M, Lin Y, Xu Z, Yan K, Adams K. Artificial intelligence for science in quantum, atomistic, and continuum systems. Foundations and Trends® in Machine Learning. 2025 Jul 20;18(4):385-912. https://doi.org/10.1561/2200000115

[56] McIntosh TR, Susnjak T, Arachchilage N, Liu T, Xu D, Watters P, Halgamuge MN. Inadequacies of large language model benchmarks in the era of generative artificial intelligence. IEEE Transactions on Artificial Intelligence. 2025 May 13. https://doi.org/10.1109/TAI.2025.3569516

[57] Hasanzadeh F, Josephson CB, Waters G, Adedinsewo D, Azizi Z, White JA. Bias recognition and mitigation strategies in artificial intelligence healthcare applications. NPJ Digital Medicine. 2025 Mar 11;8(1):154. https://doi.org/10.1038/s41746-025-01503-7

[58] Alqahtani N, Wafula Z. Artificial intelligence integration: Pedagogical strategies and policies at leading universities. Innovative Higher Education. 2025 Apr;50(2):665-84. https://doi.org/10.1007/s10755-024-09749-x

[59] Xu Y, Liu X, Cao X, Huang C, Liu E, Qian S, Liu X, Wu Y, Dong F, Qiu CW, Qiu J. Artificial intelligence: A powerful paradigm for scientific research. The Innovation. 2021 Nov 28;2(4). https://doi.org/10.1016/j.xinn.2021.100179

[60] Galante N, Cotroneo R, Furci D, Lodetti G, Casali MB. Applications of artificial intelligence in forensic sciences: C urrent potential benefits, limitations and perspectives. International journal of legal medicine. 2023 Mar;137(2):445-58. https://doi.org/10.1007/s00414-022-02928-5

[61] Sheikh H, Prins C, Schrijvers E. Artificial intelligence: definition and background. InMission AI: The new system technology 2023 Jan 31 (pp. 15-41). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-031-21448-6_2

[62] Stone P, Brooks R, Brynjolfsson E, Calo R, Etzioni O, Hager G, Hirschberg J, Kalyanakrishnan S, Kamar E, Kraus S, Leyton-Brown K. Artificial intelligence and life in 2030: the one hundred year study on artificial intelligence. arXiv preprint arXiv:2211.06318. 2022 Oct 31.

[63] Taeihagh A. Governance of artificial intelligence. Policy and society. 2021 Jun;40(2):137-57. https://doi.org/10.1080/14494035.2021.1928377

[64] Kulkarni S, Seneviratne N, Baig MS, Khan AH. Artificial intelligence in medicine: where are we now?. Academic radiology. 2020 Jan 1;27(1):62-70. https://doi.org/10.1016/j.acra.2019.10.001

[65] Giuggioli G, Pellegrini MM. Artificial intelligence as an enabler for entrepreneurs: a systematic literature review and an agenda for future research. International Journal of Entrepreneurial Behavior & Research. 2023 May 4;29(4):816-37. https://doi.org/10.1108/IJEBR-05-2021-0426