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Determinants of Public Acceptance and Adoption of Green Artificial Intelligence: An Empirical Investigation of Behavioral, Trust, and Policy Drivers

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Abstract **— The rapid escalation in computational complexity and energy demands of modern artificial intelligence (AI) has sparked widespread concern over its global environmental footprint, positioning "Green AI" as a critical paradigm for sustainable technological transformation. While technical innovations in algorithmic efficiency and green data center operations have progressed rapidly, widespread real-world adoption critically hinges upon public awareness, consumer willingness, and societal trust. This study investigates the behavioral, cognitive, and governance determinants governing the public acceptance and adoption of Green AI technologies. Grounded in the Technology Acceptance Model (TAM) and environmental behavior theories, an empirical cross-sectional investigation was conducted with N = 140 digitally active respondents across diverse occupational sectors in India, utilizing a structured 21-item survey instrument. Non-parametric Spearman's rank correlation analysis was deployed to evaluate the hypothesized relationships at α = 0.05. The empirical findings reveal that ethical and systemic trust in AI automated decision-making and technology providers constitutes the single most decisive driver of adoption (ρ = 0.874, p < 0.001), closely followed by perceived usefulness in mitigating urban pollution and environmental degradation (ρ = 0.866, p < 0.001). Personal environmental concern (ρ = 0.759, p < 0.001) and baseline awareness of AI's energy footprint (ρ = 0.629, p < 0.001) also exhibit robust, statistically significant positive associations. Crucially, while 100% of participants expressed deep environmental concern, only 89.29% were cognizant of AI's physical computational footprint, exposing a distinct digital carbon literacy gap. Furthermore, 87.14% strongly endorsed mandatory carbon footprint labeling on AI systems, and 87.86% supported government subsidies for green computing alternatives. These empirical benchmarks demonstrate that digital sustainability transitions cannot rely solely on algorithmic optimizations; they demand institutional trust calibration, visible efficiency gains, and standardized eco-transparency frameworks.**

Index Terms—Green AI, Sustainable Computing, Technology Acceptance Model (TAM), Trust in Artificial Intelligence, AI Carbon Footprint Labeling, Environmental Policy, Spearman Rank Correlation.

I. INTRODUCTION

A. The Paradox of AI Expansion: Compute Arms Race vs. Climate Goals

Artificial Intelligence (AI) has experienced unprecedented exponential advancement over the past decade, permeating virtually every stratum of contemporary socioeconomic activity. From real-time recommendation engines and autonomous vehicular navigation to deep scientific exploration and generative foundation models, AI systems are re-architecting global productivity paradigms [1]. However, this intellectual acceleration is accompanied by an acute ecological paradox. The pervasive pursuit of state-of-the-art predictive performance has catalyzed a ferocious "compute arms race," wherein frontier model architectures demand staggering quantities of specialized silicon processing, megawatts of grid electricity, and millions of liters of potable water for hyperscale data center thermal dissipation [6], [15].

Recent life-cycle assessments indicate that training a single cutting-edge transformer model can generate hundreds of metric tons of carbon dioxide equivalent (CO_2e), exceeding the lifetime emissions of multiple conventional combustion automobiles [15]. As foundation models transition from sporadic research training runs to billions of daily continuous inference executions worldwide, the cumulative operational energy consumption of the AI sector threatens to rival the aggregate power demand of

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medium-sized sovereign nations [1]. This trajectory places artificial intelligence in direct tension with international decarbonization mandates and the United Nations Sustainable Development Goals (SDGs), notably SDG 7 (Affordable and Clean Energy), SDG 12 (Responsible Consumption and Production), and SDG 13 (Climate Action).

B. The Paradigm Shift from Red AI to Green AI

In response to this unsustainable computational trajectory, the international computing community has formulated the conceptual paradigm of "Green AI" [1], [24]. In contrast to conventional "Red AI"—which relentlessly pursues marginal gains in empirical benchmark accuracy irrespective of computational, energetic, and environmental costs—Green AI establishes computational efficiency, carbon minimization, and equitable resource consumption as core evaluation metrics of algorithmic success [6], [23].

The conceptual scope of Green AI operates across two interdependent, mutually reinforcing dimensions [1], [24]: (1) AI for Sustainability (utilizing intelligent systems as optimization instruments to reduce external greenhouse emissions, manage renewable energy grids, streamline urban traffic, and automate municipal waste recycling), and (2) Sustainability of AI (engineering algorithmic model compression, quantization, weight pruning, and green data center architectures to minimize the intrinsic footprint of AI hardware and software pipelines) [6], [14], [23].

C. The Demand-Side Dilemma and Problem Statement

While technical research into algorithmic greenness and hardware acceleration has proliferated, an overwhelming majority of contemporary scholarship remains confined to supply-side engineering formulations [24]. In stark contrast, the demand-side societal and behavioral dynamics governing whether end-users, enterprises, and institutions will voluntarily embrace, prioritize, and pay for Green AI alternatives remain severely under-investigated [8], [24].

This demand-side vacuum is characterized by three critical systemic vulnerabilities: (1) an acute public awareness deficit, whereby consumers utilize compute-intensive digital services without understanding their hidden environmental ramifications [8]; (2) a complete absence of standardized eco-labeling or certified carbon disclosures, preventing conscientious consumers from distinguishing energy-frugal algorithms from compute-wasteful counterparts [20]; and (3) a severe trust deficit, wherein users exhibit skepticism toward autonomous algorithmic decisions in energy management alongside widespread cynicism regarding corporate "greenwashing" [17]. Unless these behavioral, cognitive, and governance bottlenecks are empirically deciphered, supply-side technical efficiencies risk failing to translate into tangible societal decarbonization.

D. Research Objectives and Hypotheses

To resolve this critical empirical gap, this study executes a structured quantitative investigation into the behavioral determinants of Green AI adoption. The specific objectives are: (1) o measure baseline public awareness of Green AI and AI energy consumption; (2) to assess personal environmental concern and active carbon mitigation habits; (3) to evaluate perceived usefulness regarding Green AI's capacity to resolve urban and ecological challenges; (4) to quantify public trust in AI automated decision-making and technology corporations; and (5) to establish the empirical relationships between these independent cognitive constructs and the resultant willingness to adopt Green AI technologies.

Formally, this study tests the following hypotheses using non-parametric inferential statistics at $\alpha = 0.05$:

- Null Hypothesis (H0): Public awareness, environmental concern, trust, and perceived usefulness do not have a statistically significant positive relationship with the acceptance and adoption of Green Artificial Intelligence technologies.
- Alternative Hypothesis (H1): Public awareness, environmental concern, trust, and perceived usefulness exhibit statistically significant, strong positive relationships with the acceptance and adoption of Green Artificial Intelligence technologies.

E. Paper Structure

The remainder of this paper is organized as follows: Section II synthesizes relevant literature and establishes the theoretical framework. Section III details the quantitative methodology, sampling framework, and analytical pipeline. Section IV presents empirical results and hypothesis testing. Section V discusses strategic and policy implications. Section VI outlines limitations and future research scope, and Section VII concludes the paper.

II. LITERATURE REVIEW & THEORETICAL FRAMEWORK

A. Lifecycle Analysis and the Dual Footprint of AI

Understanding the operational dynamics of Green AI necessitates a rigorous multi-lifecycle perspective. Huang and Gopal [1] established a holistic multidisciplinary framework demonstrating that an AI model's ecological footprint extends far beyond the active training phase, encompassing raw material extraction for silicon substrates, continuous data ingestion, cooling infrastructure, inference-phase latency, and hardware retirement. In their extensive bibliometric synthesis of over 2,000 academic publications, Raman et al. [24] identified five major research clusters in sustainable computing: energy-efficient hardware, ecological monitoring, sustainable data center management, algorithmic ethics, and supply chain greening. Their findings revealed that while technical engineering studies represent over 80% of published work, empirical investigations into consumer attitudes, adoption willingness, and behavioral psychology remain remarkably scarce [24].

The urgency of this discourse is amplified by the emergence of Generative AI (GenAI). Moravec, Gavurova, and Kovac [15] demonstrated that the explosive proliferation of large language models and multi-modal diffusion architectures has triggered unprecedented computational demands. They cautioned that without rigorous efficiency standards and decarbonized grid infrastructure, the indirect carbon savings achieved by AI-

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assisted optimization could be completely negated by the direct emissions generated during model execution [15]. Rajath and Vivian [23] categorized technical mitigation into three hierarchical tiers: algorithmic interventions (pruning, 8-bit/4-bit quantization, knowledge distillation), architectural optimization (edge processing, neuromorphic computing, renewable microgrids), and downstream sectoral optimization [6], [23].

B. *Sectoral Applications and Environmental Optimizations*

The potential of Green AI to deliver measurable ecological remediation is extensively documented across key industrial sectors. In smart energy grids, Mastoi et al. [14] and Preethi et al. [21] proved that deep reinforcement learning and federated edge computing optimize renewable energy integration, balance fluctuating solar/wind loads, and minimize transmission dissipation in IoT ecosystems. In urban mobility, Muyombo and Vadapalli [16] demonstrated that adaptive AI traffic signalization reduces vehicular idling emissions by over 18%, corroborated by Obaid et al. [18] through unmanned aerial vehicle (UAV) traffic analysis and Khreis et al. [7] through urban low-traffic neighborhood emission modeling.

In solid and municipal waste ecosystems, Lakhouit [10], Priyanka et al. [22], Wang et al. [32], Khan et al. [5], and Thomaz et al. [30] verified that computer-vision sorting, automated recycling robotics, and machine-learning leachate forecasting achieve substantial reductions in municipal methane emissions. Furthermore, Kadoglu and Yac [3] deployed Green AI quantile boosting for energy-efficient real estate valuation, Huda et al. [2] documented AI adoption in South Asian agricultural sustainability, and Singh and Reddy [28], Zareba and Danek [34], and Zhao and Ye [35] verified that edge AI and explainable AI (XAI) provide real-time air pollution mitigation across urban innovation zones.

C. *Behavioral Dynamics, Trust Calibration, and Green Tech Acceptance*

To model user acceptance, this study draws upon the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), synthesized with environmental psychology [4], [9], [12], [33]. In classical TAM, perceived usefulness (PU) and perceived ease of use (PEOU) predict behavioral intention. However, Kranz and Picot [9] demonstrated that in green information systems (Green-IS), personal environmental concern acts as both a direct behavioral catalyst and a potent moderator of perceived utility.

Trust constitutes an essential behavioral gateway. In complex autonomous systems, users must reconcile perceived benefits with perceived risks [12]. Nordhoff and Hagenzieker [17] ighlighted that trust calibration in autonomous algorithms is fragile; over-trust induces complacency, whereas under-trust triggers outright rejection. Li and Li [12] established that user acceptance of AI services is deeply governed by perceived control and algorithmic transparency. In consumer marketing, Klesel and Messer [8] documented that awareness of AI energy consumption directly influences user responsibility attribution, while Salem [25], [26] identified that pro-ecological intentions among Gen-Z digital natives strongly dictate green technology adoption intentions when backed by ethical governance. Kalra et al. [4] and Wilson [33] reinforced that customer readiness for eco-friendly digital products requires institutional support, peer influence, and transparent benefit verification [11], [31].

D. *Institutional Governance, Policy Frameworks, and Corporate ESG*

At the macro-systemic level, digital sustainability requires supportive institutional and policy frameworks. Peng et al. [20] analyzed the dual mechanism of government subsidies and consumer eco-consciousness in digital green transformation, demonstrating that regulatory financial incentives substantially accelerate platform-level green adoption when aligned with consumer demand signals. Lv [13] established that AI adoption elevates corporate Environmental, Social, and Governance (ESG) performance across BRICS economies, provided that innovation is anchored by green finance and regulatory oversight. Omoyajowo et al. [19] verified that leadership commitment and regulatory pressure dictate green computing policy compliance in corporate settings, while Sulich and Kozar [29] ocumented the rapid emergence of green ICT job categories. Furthermore, Sharma et al. [27] demonstrated that the barriers hindering green building rating systems—namely high upfront perception costs and verification deficits—directly mirror the challenges facing consumer-facing Green AI certification.

E. *Identification of Research Gaps*

The synthesized literature reveals a clear academic dichotomy: extensive research addresses algorithmic engineering (how to make models computationally leaner) and macro-policy theory (how governments should frame digital transformation), yet empirical data quantifying how individual cognitive awareness, personal environmental ethics, and corporate trust interact to drive actual consumer adoption remains critically deficient. This paper directly bridges this gap through an empirical investigation of demand-side determinants.

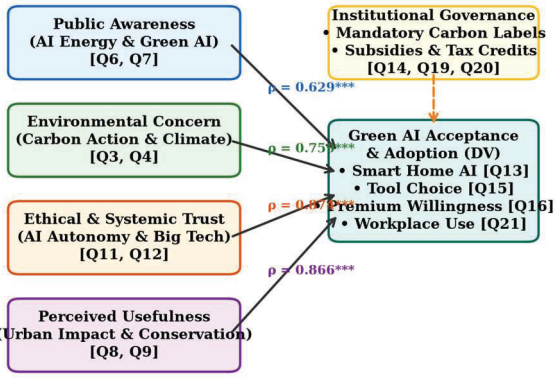

Fig. 1.
Conceptual Research Framework: Determinants of Green AI Acceptance and Adoption, illustrating independent cognitive constructs, the central acceptance construct, and moderating institutional governance mechanisms.

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III. RESEARCH METHODOLOGY

A. Research Approach and Epistemological Framework

This investigation adopts a quantitative, deductive research approach grounded in positivist epistemology [4], [33]. Positivism posits that social and behavioral phenomena can be systematically operationalized through measurable empirical constructs, structured instruments, and mathematical hypothesis testing. Given that the core objective is to quantify the strength and direction of relationships between cognitive determinants (awareness, environmental concern, trust, usefulness) and technology acceptance, a quantitative survey design provides the necessary empirical precision and statistical generalizability.

B. Target Population and Sample Size Formulation

The target population comprises digitally literate individuals across educational and professional sectors who interact regularly with AI systems, smart devices, and cloud-based digital infrastructure. To establish mathematical rigor in sample determination, the study applied the benchmark formulation established by Krejcie and Morgan (1970) [4]:

$$S = [\chi^2 \cdot N \cdot P \cdot (1 - P)] / [d^2 \cdot (N - 1) + \chi^2 \cdot P \cdot (1 - P)] \quad (1)$$

where S represents the required sample size, χ^2 is the chi-square value for 1 degree of freedom at the desired confidence level (3.841 for 95% confidence, $\alpha = 0.05$), N is the defined target population cohort (N = 220 within the institutional and professional sampling frame), P is the assumed population proportion exhibiting the characteristic (assumed at 0.50 to guarantee maximum variance and sample conservatism), and d is the acceptable margin of error (d = 0.05). Substituting these standardized parameters yields:

$$S = [3.841 \cdot 220 \cdot 0.5 \cdot 0.5] / [(0.05)^2 \cdot 219 + 3.841 \cdot 0.5 \cdot 0.5] \approx 140.2 \quad (2)$$

Consequently, a sample threshold of S = 140 was established. The empirical survey was widely disseminated through multi-channel digital networks, yielding exactly N = 140 fully completed, valid responses with zero missing attributes, fulfilling the Krejcie and Morgan criterion with 100% data integrity.

C. Demographic Profile of the Sample

The sampling distribution captures a highly relevant demographic cohort of early digital adopters and future decision-makers, summarized in Table I. Students represent the largest occupational cohort (72.14%, n = 101), followed by Corporate Employees (15.71%, n = 22), Self-Employed professionals (5.71%, n = 8), Business Owners (4.29%, n = 6), and Government Personnel (2.14%, n = 3). In terms of age stratification, 62.86% (n = 88) belong to the 18–24 bracket, 26.43% (n = 37) to the 25–34 bracket, 7.14% (n = 10) to the 35–44 bracket, and 3.57% (n = 5) are aged 45 and above. This profile aligns with Salem's [25], [26] findings that Gen-Z and young professionals represent the vanguard of digital sustainability transitions.

TABLE I. **DEMOGRAPHIC COMPOSITION OF SURVEY RESPONDENTS (N = 140)**

Demographic Variable	Category / Strata	Freq. (n)	Pct. (%)
Occupation	Students	101	72.14%
	Corporate Employees	22	15.71%
	Self-Employed	8	5.71%
	Business Owners	6	4.29%
	Government Employees	3	2.14%
Age Stratification	18–24 years	88	62.86%
	25–34 years	37	26.43%
	35–44 years	10	7.14%
	45–54 years	3	2.14%
	55+ years	2	1.43%
Total Sample	**Valid Verified Records**	**140**	**100.00%**

D. Survey Instrument Design and Operationalization

Data was collected using a structured 21-item questionnaire organized into eight conceptual dimensions: Demographics (Q1–Q2), Environmental Awareness & Concern (Q3–Q5), Green AI Familiarity (Q6–Q7), Perceived Usefulness (Q8–Q10), Trust & Governance (Q11–Q12), Adoption Willingness & Behavioral Intent (Q13–Q17), Policy Support (Q18–Q20), and Professional Integration (Q21). Attitudinal items were operationalized using a balanced 5-point Likert scale (1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree), while factual knowledge was captured via binary (Yes/No) measures.

E. Statistical Analysis Pipeline

The quantitative pipeline was executed in Python 3.12 utilizing pandas (v2.3.1) for data cleansing and aggregation, scipy.stats (v1.18.1) for non-parametric inferential hypothesis testing, and matplotlib (v3.11.2) for figure rendering. Composite scores for each theoretical construct were calculated as the unweighted arithmetic mean of their constituent survey indicators:

$$C_k = (1 / m_k) \cdot \sum_{j=1}^{m_k} x_{ij} \quad (3)$$

where C_k is the composite construct score for respondent i, m_k is the number of indicator items operationalizing construct k, and x_{ij} is the numerical Likert score for item j. Given that survey responses represent ordinal data, non-parametric Spearman's rank correlation coefficient (ρ) was selected as the rigorous statistical test:

$$\rho = 1 - [6 \cdot \sum d_i^2] / [n \cdot (n^2 - 1)] \quad (4)$$

where d_i is the difference between the ranks of each pair of composite observations, and n is the sample size (n = 140). Spearman's correlation makes no parametric normality assumptions, is robust against skewness, and precisely assesses monotonic associations.

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IV. EMPIRICAL RESULTS & HYPOTHESIS TESTING

A. Descriptive Evaluation of Survey Constructs

The descriptive analysis yields compelling baseline insights into public consciousness regarding digital sustainability. Regarding general environmental concern, an extraordinary 100.00% of respondents agreed (41.43%, n = 58) or strongly agreed (58.57%, n = 82) that global environmental degradation and climate change are critical concerns (Q4), with 65.71% actively working to reduce their personal carbon footprints (Q3). When evaluating general technological literacy, 92.14% felt confident in their comprehension of AI systems (Q5).

In terms of Green AI awareness, 92.86% (n = 130) reported baseline familiarity with the concept of eco-friendly AI (Q6). However, a distinct gap emerged when evaluating physical resource awareness: 89.29% (n = 125) were aware of AI's substantial electricity and water consumption, leaving 10.71% completely uninformed (Q7). Regarding perceived usefulness, 84.28% agreed that AI systems can significantly mitigate urban traffic and pollution (Q8), 82.14% agreed that Green AI makes personal conservation easier (Q9), and 77.85% affirmed that the environmental benefits of Green AI outweigh its computational footprint (Q10).

B. Public Sentiments on Trust, Governance, and Economic Drivers

The study captured profound empirical insights regarding trust calibration and economic readiness. While 80.71% of respondents expressed trust in AI automated decision-making for domestic energy optimization (Q11), trust in technology corporations to voluntarily prioritize environmental sustainability over profit margins was lower and accompanied by marked skepticism (19.29% expressing neutral or dissenting views, Q12).

Crucially, public willingness to adopt Green AI translates into tangible economic commitments: 85.00% prefer choosing eco-friendly AI tools over conventional ones (Q15), and 78.57% (n = 110) stated they are actively willing to pay a moderate financial premium for verified green AI services (Q16). Furthermore, 86.43% acknowledged a personal moral obligation to adopt energy-efficient AI (Q18), while 72.86% acknowledged willingness to accept minor computational inconveniences or latency trade-offs for green alternatives (Q17). Support for systemic intervention was overwhelming: 87.85% endorsed government subsidies and tax incentives (Q19), 87.14% favored public investment in green infrastructure (Q14), and 87.14% demanded mandatory carbon footprint labeling on commercial AI models (Q20), as summarized in Table IV.

TABLE II. **CONSTRUCT OPERATIONALIZATION, SURVEY ITEM MAPPING, AND DESCRIPTIVE INDICES**

Construct Name	Constituent Items	Core Operational Focus	Mean	Std. Dev.
Public Awareness	Q6, Q7	Baseline Green AI knowledge & AI energy footprint	0.911*	0.218
Environmental Concern	Q3, Q4	Personal climate concern & carbon mitigation action	4.214	0.584
Ethical & Systemic Trust	Q11, Q12	Trust in AI decisions & corporate green claims	4.043	0.687
Perceived Usefulness	Q8, Q9	Perceived efficacy in pollution & resource reduction	4.179	0.642
Green AI Acceptance (DV)	**Q13, Q15, Q16, Q21**	**Willingness to adopt, pay premium, & prioritize**	**4.155**	**0.612**

[a] *Note: Awareness construct was computed across binary operational items (0 = Unaware, 1 = Aware), yielding an index scale [0–1], whereas remaining constructs operate on standard 5-point Likert metrics [1–5].

TABLE III. **PUBLIC ACCEPTANCE, ECONOMIC, AND POLICY SENTIMENTS (N = 140)**

Survey Indicator Statement	Item	Agree / Str. Agree	Neutral	Disagree
Government Subsidies & Tax Credits	Q19	87.85% (123)	12.14% (17)	0.00% (0)
Mandatory AI Carbon Footprint Labeling	Q20	87.14% (122)	12.14% (17)	0.71% (1)
Moral Duty to Choose Green AI	Q18	86.43% (121)	11.43% (16)	2.14% (3)
Active Preference for Green AI Tools	Q15	85.00% (119)	14.29% (20)	0.71% (1)
Willingness to Pay Green Premium	Q16	78.57% (110)	16.43% (23)	5.00% (7)
Acceptance of Latency/Inconvenience	Q17	72.86% (102)	24.29% (34)	2.86% (4)

C. Non-Parametric Correlation Analysis and Hypothesis Resolution

To test the research hypotheses, Spearman's rank correlation coefficients (ρ) were computed between each of the four independent composite constructs and the dependent composite construct of Green AI Acceptance. The complete correlation matrix and statistical hypothesis testing outcomes are presented in Table III.

TABLE IV. **SPEARMAN'S RANK CORRELATION HYPOTHESIS TESTING MATRIX (N = 140)**

Independent Variable	Dependent Variable	Spearman (ρ)	p-value	Significance	Hypothesis Outcome
Ethical & Systemic Trust	Green AI Acceptance	0.874	< 0.001	Significant (p < 0.001)	H0 Rejected (Rank 1)
Perceived Usefulness	Green AI Acceptance	0.866	< 0.001	Significant (p < 0.001)	H0 Rejected (Rank 2)
Environmental Concern	Green AI Acceptance	0.759	< 0.001	Significant (p < 0.001)	H0 Rejected (Rank 3)
Public Awareness	Green AI Acceptance	0.629	< 0.001	Significant (p < 0.001)	H0 Rejected (Rank 4)

As demonstrated in Table III, all four correlation coefficients are statistically significant at $p < 0.001$, decisively surpassing the $\alpha = 0.05$ significance threshold. Consequently, the Null Hypothesis (H0) is definitively rejected, and the Alternative

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Hypothesis (H1) is validated. The empirical ranking reveals that Ethical Trust (ρ = 0.874) represents the most powerful single driver of acceptance, followed closely by Perceived Usefulness (ρ = 0.866), Environmental Concern (ρ = 0.759), and Public Awareness (ρ = 0.629).

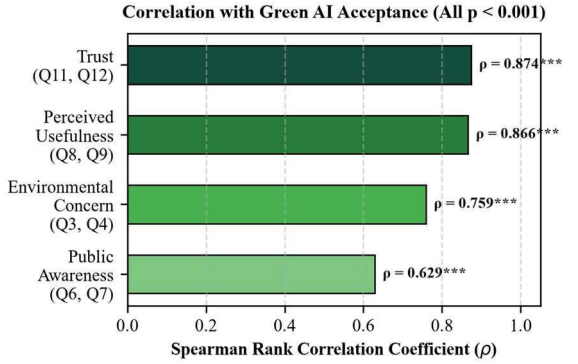

Fig. 2.
Non-parametric Spearman Rank Correlation Coefficients (ρ) between independent theoretical constructs and Green AI Acceptance (All relationships statistically significant at p < 0.001).

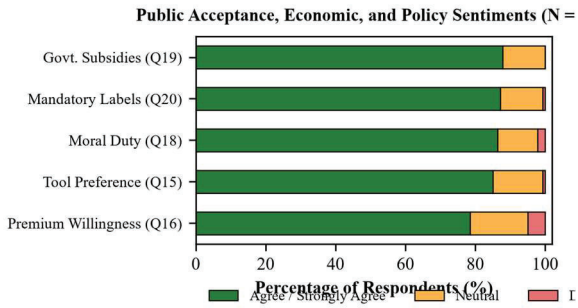

Fig. 3.
Clustered Public Sentiments Regarding AI Governance, Economic Incentives, and Moral Obligation across 140 surveyed respondents.

V. DISCUSSION & STRATEGIC IMPLICATIONS

A. Trust as the Primary Gatekeeper of Green AI Adoption

The empirical finding that Ethical and Systemic Trust constitutes the strongest predictor of Green AI acceptance (ρ = 0.874, p < 0.001) represents a pivotal contribution to technology acceptance theory. In classical implementations of TAM, perceived usefulness traditionally dominates behavioral intention [4], [9]. However, in autonomous and algorithmic sustainability systems, end-users are required to surrender real-time control to intelligent agents—such as allowing an AI model to autonomously govern home heating, regulate appliances, or manage enterprise workloads [12], [17].

Under these conditions, trust functions as a mandatory behavioral gatekeeper. If users suspect that automated energy management compromises comfort, breaches private data, or that corporate sustainability claims constitute self-serving "greenwashing," adoption collapses regardless of technical sophistication. This aligns directly with Nordhoff and Hagenzieker's [17] trust calibration framework and Li and Li's [12] findings on perceived control, underscoring that developers cannot treat trust as a peripheral marketing concern; it is the structural cornerstone of adoption.

B. The Superiority of Tangible Utility over Abstract Environmentalism

The near-equal dominance of Perceived Usefulness (ρ = 0.866, p < 0.001) compared to general Environmental Concern (ρ = 0.759) offers critical tactical guidance. While 100% of respondents expressed general concern regarding global environmental crises, generalized eco-consciousness does not automatically convert into digital tool adoption unless the practical utility of the tool is immediately visible. Consumers demand clear, quantifiable proof that adopting a Green AI tool delivers tangible efficiency gains—such as visible reductions in electric utility bills, measurable commute time optimizations, or certified carbon offsets [8], [20]. abstract environmental rhetoric without verifiable utility fails to trigger long-term behavioral change.

C. The Digital Carbon Literacy Deficit

A critical insight uncovered in this study is the cognitive dissonance between general environmental concern and digital carbon literacy. While 100% of participants expressed deep ecological worry and 92.86% recognized the phrase "Green AI," over 10.7% remained entirely oblivious to the fact that artificial intelligence consumes physical energy and water resources. This "invisible emissions" dilemma echoes Klesel and Messer's [8] observation that digital consumption is cognitively detached from environmental degradation in the public mind. Users understand the emissions of combustion vehicles or plastic packaging because they are tangible; cloud-based AI inference, by contrast, feels weightless and clean. Bridging this literacy gap through targeted public education is essential to activating consumer demand for green computing.

D. Strategic Implications for Technology Developers and Enterprises

For commercial AI vendors, cloud platform architects, and software enterprises, these empirical results provide an actionable roadmap: (1) Prioritize Efficiency by Design: Transition from parameter-bloated foundation models to compact, task-specific, distilled architectures running on energy-efficient edge silicon [6], [28]; (2) Implement Front-End Carbon Telemetry: Embed visible, real-time computational energy indicators directly into consumer software interfaces (e.g., displaying watt-hours or carbon grams consumed per query session); and (3) Guarantee Algorithmic Explainability: Provide transparent rationale for automated energy-saving decisions to avoid user alienation and preserve calibrated trust [12], [34].

E. Policy, Regulatory, and Governance Recommendations

The overwhelming public consensus in favor of institutional governance—with 87.14% mandating carbon labeling and 87.86% backing subsidies—demands decisive regulatory intervention:

1) Mandatory Standardized AI Eco-Labeling: Mirroring energy-efficiency ratings in consumer appliances (e.g.,

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ENERGY STAR or EU Energy Labels), regulatory bodies must institute mandatory standardized carbon disclosure ratings for public AI models, detailing lifecycle compute watt-hours and carbon intensity [20], [27].

2) Fiscal Subsidies and Tax Credits: Governments should implement targeted tax relief and procurement incentives for institutions and enterprises that demonstrably transition to certified green computing architectures, verifying Peng et al.'s [20] ual-subsidy model.

3) Curricular Integration and Digital Literacy: Higher educational institutions must integrate green computing and digital carbon literacy across computer science and management curricula to cultivate the next generation of eco-conscious software engineers and corporate leaders [29], [33].

VI. CHALLENGES, LIMITATIONS & FUTURE SCOPE

A. Methodological and Sampling Boundaries

To maintain scholarly integrity, several methodological constraints must be acknowledged. First, the investigation relies upon self-reported cross-sectional survey data, which is susceptible to social desirability bias (participants overstating their environmental virtue) and acquiescence bias. Second, the sample design utilized convenience and purposive sampling centered in Maharashtra, India. Although perfectly aligned with the Krejcie and Morgan benchmark (N = 140), the heavy concentration of students (72.14%) and individuals aged 18–24 (62.86%) primarily characterizes the attitudes of Gen-Z digital natives. While this cohort represents the primary future demographic of technological consumption [25], [26], findings should be generalized to older or rural populations with appropriate academic caution.

B. Scope of Operationalized Variables

The quantitative model intentionally concentrated on four primary cognitive and psychological predictors (awareness, concern, trust, usefulness). Consequently, other potentially impactful exogenous factors—such as disposable income levels, regional electrical grid carbon intensity, software switching costs, and institutional organizational culture [19]—were not included in the regression matrix.

C. Future Research Directions

Future scholarship should expand upon these findings through three vital avenues: (1) Longitudinal and Field Experimental Designs: Deploying real-world behavioral trials that track actual consumer tool-selection patterns when exposed to live digital carbon labels; (2) Multi-Regional Cross-Cultural Comparisons: Replicating the survey framework across diverse geographic, regulatory, and cultural jurisdictions (e.g., comparing EU, North American, and Asian populations); and (3) Machine Learning Predictive Modeling: Implementing non-linear classification algorithms (random forests, gradient boosting) to map complex, non-linear interaction effects between user demographics, switching friction, and adoption propensity.

VII. CONCLUSION

As artificial intelligence becomes deeply interwoven with the fabric of global economic activity, its burgeoning computational energy and environmental footprint can no longer remain an unaddressed externality. Green AI provides the indispensable technical paradigm to reconcile algorithmic power with planetary sustainability. However, this empirical study proves that technological feasibility alone cannot drive systemic transition. By rigorously examining 140 surveyed respondents through non-parametric Spearman rank correlation, this paper demonstrates that Ethical and Systemic Trust ($\rho = 0.874$, $p < 0.001$) and Perceived Practical Usefulness ($\rho = 0.866$, $p < 0.001$) act as the primary engines of Green AI acceptance, decisively outranking baseline awareness.

Furthermore, the strong societal willingness to pay a green premium (78.57%) and the overwhelming mandate for mandatory carbon labeling (87.14%) and government subsidies (87.86%) signal that the public is prepared for digital sustainability—provided that technological systems are transparent, verified, and demonstrably beneficial. By bridging the critical divide between algorithmic engineering and human behavioral dynamics, this research establishes vital empirical foundation for technology developers, corporate leaders, and policymakers striving to forge a truly sustainable digital future.

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