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THE ROLE OF ARTIFICIAL INTELLIGENCE IN CARBON PRICING POLICIES: ECONOMIC AND ENVIRONMENTAL IMPLICATIONS

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Abstract

The use of AI in carbon pricing policies can offer both opportunities and future challenges for the United States as it acts on climate change. This study examines experts' perspectives on AI's potential to enhance the effectiveness, enforcement, and equity of carbon pricing. Based on a survey of 200 U.S. experts, the research explores key factors shaping support for AI-driven climate policies, including technological feasibility, public acceptance, and regulatory hurdles. Statistical analyses, including chi-square, ANOVA, correlation, multiple regression, and logistic regression, reveal that AI's policy role is most influenced by knowledge and trust, whereas algorithmic bias, data limitations, and legal uncertainties remain significant barriers.

The findings highlight urgent U.S. priorities in climate resilience, digital infrastructure, and environmental justice, offering critical insights into the social and technical readiness for AI-integrated carbon policies. Furthermore, the study identifies disparities in expert opinions, with technologists emphasizing innovation while policymakers stress accountability. Public-private collaboration and interdisciplinary research are deemed essential to overcoming implementation challenges. The study also underscores the need for transparent governance frameworks to address ethical concerns, mitigate risks of automation bias, and foster public trust. By identifying key drivers of policy acceptance, this research provides actionable recommendations for lawmakers, including adaptive regulations and stakeholder engagement strategies.

Ultimately, this study advances understanding of AI's role in climate action, informing both policy practitioners and academic researchers while paving the way for responsible innovation in carbon pricing mechanisms. Future research should explore real-world case studies and international comparisons to refine best practices for AI-enabled climate governance.

Keywords

Artificial Intelligence, Carbon Pricing, Climate Policy, United States, Environmental Justice, Machine Learning, Trust in AI, Algorithmic Bias, Policy Support, Digital Climate Governance

I-INTRODUCTION

With the global economy, needing to decarbonize quickly, more attention is now being given to carbon pricing as a key climate policy approach. Carbon taxes and emissions trading schemes (ETS) are thought by many to be successful ways to cut down on greenhouse gases (Abrell et al, 2022; Tiwari et al, 2021). Such approaches can run into problems with applying data consistently, gaining political acceptance and ensuring fairness, as no federal carbon pricing laws exist in the United States, despite increasing climate risks

(Dauvergne, 2022; Chen & Jin, 2023). Artificial intelligence (AI) provides support for switching to clean energy by helping set up, track and enforce carbon pricing systems (Kaack et al, 2022; Bolón-Canedo et al, 2024).

Recent studies suggest that AI is having a major influence in energy planning, clean manufacturing, grid design, how we deal with waste and biofuel creation. Due to advancements in machine learning, deep learning and reinforcement learning, large-scale emission data can be analyzed, unusual behavior can be recognized and this can result in prices that react to demand in real-time (Ojadi et al, 2023; Chang et al, 2023). AI makes carbon pricing instruments work better and more transparently, says research that demonstrates AI models achieve more accurate results compared to historical models (Abrell et al, 2022; Wu et al, 2022).

In the United States, including AI in carbon pricing policies supports important national concerns, for example clean energy, better digital tools, and environmental equity. Both the Inflation Reduction Act of 2022 and Executive Order 14096 have mandated stronger data systems for emissions monitoring and public accountability. AI helps accomplish these goals by making it possible to monitor emissions in real time and accommodating fair pricing for those people most affected (Hong & Xiao, 2024; Liu et al, 2022). AI is expected to aid carbon neutrality by working on renewable energy integration, raising the efficiency of energy systems and helping them cause fewer environmental problems (Zhou et al, 2024; Liu et al, 2022; Wang et al, 2024).

Even though AI has great potential, it has not been fully adopted in environmental regulation because of a number of barriers. They consist of unclear policies; restricted data use and worries about bias and pollution from AI (Tamburrini, 2022; Cowls et al, 2023; Zhang & Feng, 2024). Research has mainly ignored the impact of stakeholder perceptions such as their opinions about AI, trust, role and organization affiliation, on the support for AI integration in carbon pricing. While some studies abroad examine AI's part in reducing emissions (Ding et al, 2023; Chen et al, 2022), there are not many examples from the U.S. that look at the factors that shape policy adoption in this field. This research seeks to explore how professionals in the government, academia, technology, and sustainability sectors in the U.S. see the role that AI can play in carbon pricing. The study uses information from 200 respondents to analyze how much individuals know about AI, how much they trust AI, where they work, and their views on federal use of AI. It investigates issues like concerns about bias, problems obtaining data and concerns about regulations, by using different models to determine their effects on policy preferences.

The research helps bring new insights to the topic of AI and carbon pricing policy, contributing to debates in environmental economics, climate regulation, and AI ethics. Its research provides both analysis and practical advice for policymakers, regulators and technologists to use AI in good and ethical ways that serve the country's climate needs (Tseng & Lin, 2024; Manikandan et al, 2025; Gaur et al, 2023).

II-METHODOLOGY

A. RESEARCH DESIGN

The article utilizes a quantitative, cross-sectional survey to investigate the opinions of U.S. professionals on integrating AI with how carbon pricing is set in America. The objective of this design was to discover any connections between participants' background and work experience with their attitudes towards AI-based carbon pricing by the government. It explored what people see as the positive aspects, the problems with applying them and ethical problems such as algorithmic bias.

B. TARGET POPULATION AND SAMPLING

All professions in the target group were based in government organizations, academic research centers, private firms' organizations not supported by the government (NGOs) and think tanks from all parts of the United States. The choices were made because these people work in climate policy, sustainability, environmental science, technology, economics or regulatory affairs.

To collect data, we recruited 200 participants with both purposive and snowball sampling through networks, institutional mailing lists and social media outreach, as well as cooperation with organizations. With this approach, the sample included a wide variety of sectors and technical areas.

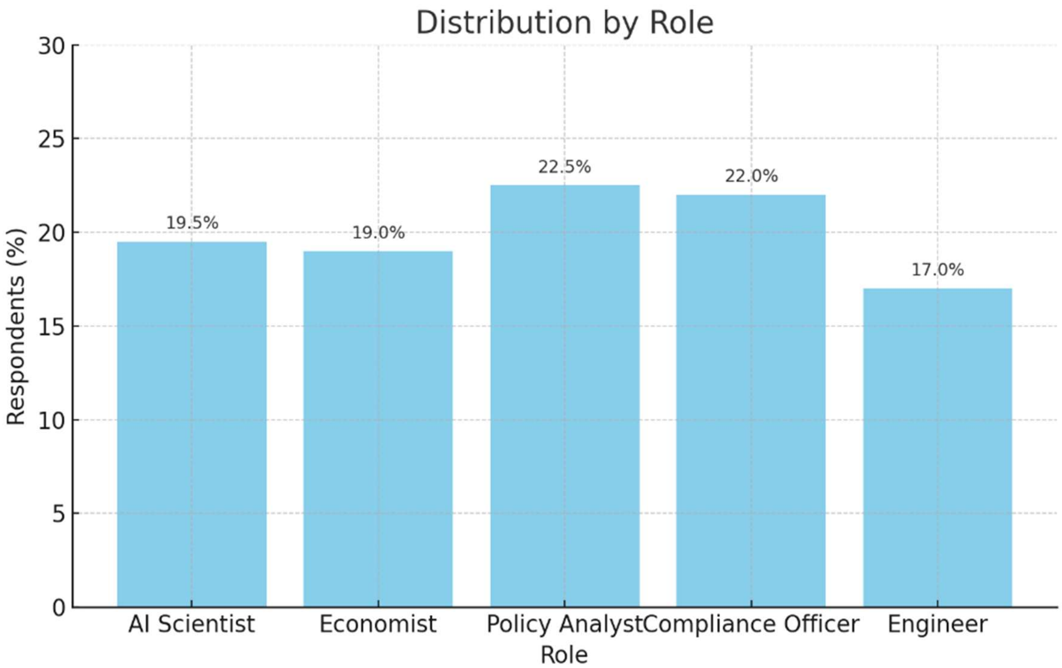

Figure 1: Distribution of Respondents by Role (N = 200)

C. METHODOLOGICAL RELEVANCE AND RESEARCH GAP

AI is now used widely in modeling energy and emissions but there is a lack of studies examining the views of U.S. professionals about using artificial intelligence in carbon pricing. It is clear from previous studies that experts are mostly concerned with the technical aspect but hardly examine issues like trust, bias and insecure regulations (Cowls et al, 2023; Tamburrini 2022).

This research addresses this need by surveying 200 experts from U.S. government agencies, universities, NGOs and industrial businesses about their views on AI and carbon pricing policy. It is among the first to examine the role of AI understanding, trust, job position and perceived bias on favoring AI use by the government. The use of ANOVA, correlation and regression in this research provides a distinct, policy-important view of AI's sociotechnical status in U.S. climate governance.

D. SURVEY INSTRUMENT

We gathered most of our data using an online questionnaire built with Google Forms. Participants answered questions on a scale and took multiple choice tests to measure their views on AI, confidence in it, knowledge and policy backing.

The questionnaire was divided into five sections:

I. Demographic and Professional Information
(e.g, age, gender organization type, job role, experience level)
II. AI Knowledge and Familiarity
(self-assessed knowledge of AI in climate policy, familiarity with carbon pricing)
III. Perceptions of AI Applications
(real-time tracking, predictive pricing, compliance monitoring)
IV. Support for Federal Integration of AI
(measured on a 5-point Likert scale)

V. Perceived Barriers and Ethical Concerns
(including data access, regulatory guidance, algorithmic bias)

A small number of domain experts were asked to use the instrument before its launch to ensure it was clear and made sense. Further improvements were done after feedback before the app was fully launched.

E. DATA COLLECTION PROCEDURE

The collection of data took place over four consecutive weeks. Before the survey began, participants were offered an informed consent statement that guarantees their personal details will not be shared and that taking part is entirely their choice. No individual data was gathered.

Electronic links to the survey were distributed and participants were urged to pass them on, allowing the sampling to spread farther without compromising sample quality.

F. DATA ANALYSIS TECHNIQUES

All statistical analysis was done with the help of IBM SPSS Statistics software. An analysis was performed on:

- **Descriptive statistics** (frequencies, percentages, means) to summarize respondent characteristics
- **Chi-square tests** to assess associations between categorical variables such as support levels across roles and organization types
- **One-way ANOVA** to evaluate differences in support levels across sectors and AI knowledge levels.
- **Pearson correlation analysis** to examine relationships between trust, AI knowledge and policy support.
- **Multiple linear regression** to identify predictors of continuous support scores.
- **Binary logistic regression** to determine the likelihood of high support for AI integration based on key factors like trust, tracking belief and bias concern.

All statistical tests used a significance threshold of $p < .05$.

G. ETHICAL CONSIDERATIONS

The study was conducted by following social science ethics and the Ethical Review Body approved it. Respondents were able to take part in the survey without obligation and the data they shared would not be linked to them and would only be used in research.

III-RESULTS

In this section, empirical results from the study are shared, gathered through a questionnaire distributed to 200 U.S.-based members of the policy, research, technology, and sustainability communities.

A. RESPONDENT CHARACTERISTICS

Respondent distribution by organization type and profession is included in Table 1 below. Many of the participants came from non-governmental organizations (24.5%), government agencies (21.5%), and private companies (18.5%). The range of organizations involved in these councils mirrors the broad group of individuals and groups interested in U.S. climate policy and AI.

The most popular professions among the group were policy analysis (22.5%) and sustainability/compliance (22.0%), the third largest group were AI/data scientists (19.5%). By combining technical, policy and research responsibilities, researchers have a complete view of how AI affects carbon pricing. Chi-square tests showed that there was no significant link between organization type and perceived AI relevance ($p = .631$), nor between role and backing for AI policy integration ($p = .147$), suggesting that opinions were similar across various groups.

Table 1: Respondent Distribution by Organization Type and Role (N = 200)

Group	Category	Frequency	Percent	p-value
Organization Type	Academic/Research Institution	35	17.5%	.631
	Government Agency	43	21.5%	
	Non-Governmental Organization (NGO)	49	24.5%	
	Private Company	37	18.5%	
	Think Tank	36	18.0%	
Role	AI/Data Scientist	39	19.5%	.147
	Economist/Researcher	38	19.0%	
	Policy Analyst/Advisor	45	22.5%	
	Sustainability/Compliance Officer	44	22.0%	
	Technical Consultant/Engineer	34	17.0%	

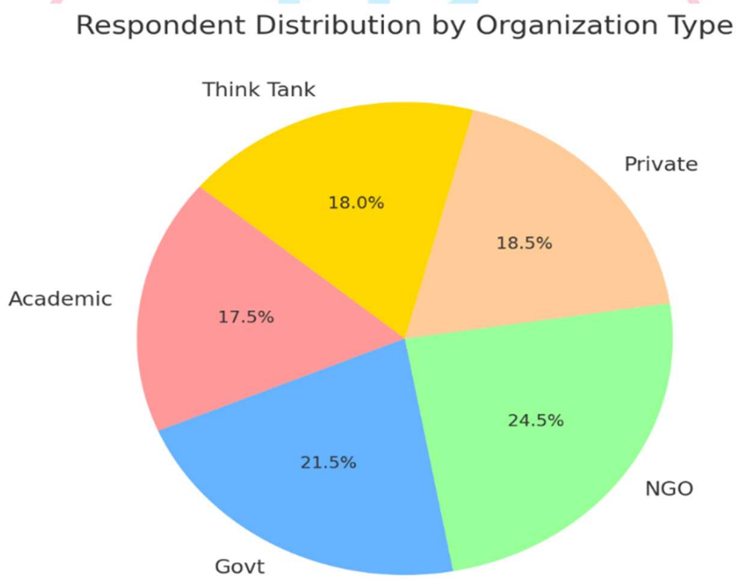

Figure 2: Respondent Distribution by Organization Type

Experience, Familiarity and Knowledge Base

Table 2 consists of data on participants' exposure to carbon pricing, the amount of AI they know and their experience levels. 26% of respondents reported over a decade of career experience in this field and an additional 22.5% said they had 6 to 10 years. 30% worked for less than 3 years which reflected the increased number of young people starting a career in this dynamic sector.

Most (76.5%) participants reported being at least somewhat familiar with U.S. carbon-pricing approaches and 31.5% were especially familiar with them. It becomes especially important as the research centers on policies.

In climate policy and AI, most participants assessed their knowledge either as moderate (43.5%) or advanced (20%), suggesting that the participants were knowledgeable. Just 9.5% of respondents said they had no knowledge of AI which was not enough to affect the study's findings. The results of chi-square tests show there are no significant links between levels of AI understanding, years of experience or familiarity with carbon pricing, suggesting that people from all experience and sector levels share AI knowledge.

Table 2: Respondent Distribution by Experience, Carbon Pricing Familiarity and AI Knowledge (N = 200)

Group	Category	Frequency	Percent	p-value
Experience Level	Less than 3 years	60	30.0%	.193
	3–5 years	43	21.5%	
	6–10 years	45	22.5%	
	More than 10 years	52	26.0%	
Carbon Pricing Familiarity	Not familiar	47	23.5%	.521
	Somewhat familiar	90	45.0%	
	Very familiar	63	31.5%	
AI Knowledge in Climate	None	19	9.5%	.288
	Basic	54	27.0%	
	Moderate	87	43.5%	
	Advanced	40	20.0%	

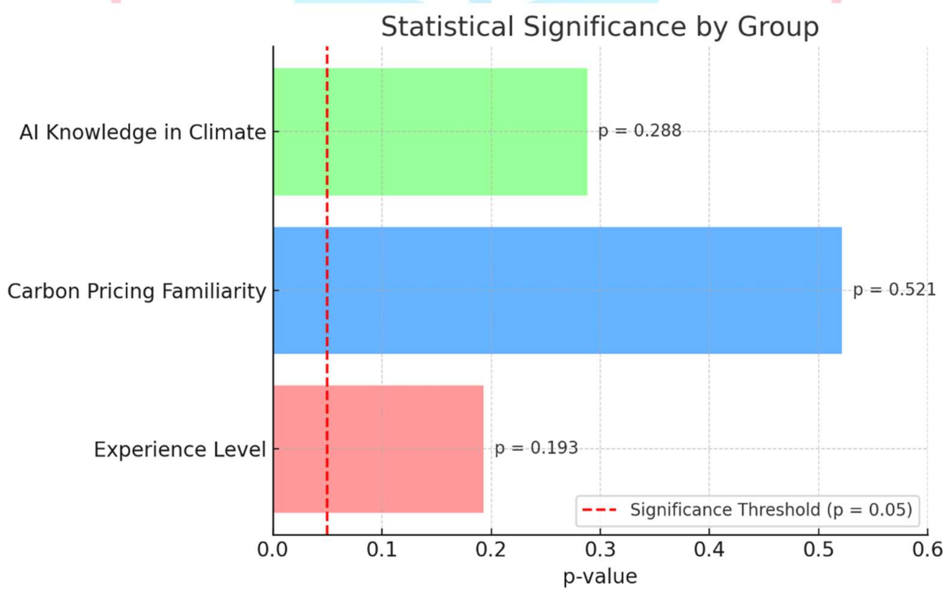

Figure 3: Statistical Significance of Group Differences Based on p-values
Note: *Red dashed line indicates the conventional threshold for statistical significance (p = 0.05).*

PERCEPTIONS OF AI EFFECTIVENESS AND POLICY SUPPORT ACROSS ROLES AND ORGANIZATIONS

According to Table 3, confidence in AI's ability to handle carbon pricing was consistent across roles and organization types, only differing slightly. Out of all our respondents, policy analysts, sustainability officers and officials from government agencies tended to report the greatest effectiveness (≥ 3.9/5). 75% of government agency participants agree that AI should be integrated into the federal government and 50% have experienced AI applications directly, testing out the tech themselves.

Those involved in shaping government policy (analysts and economists) reported mostly high and similar support for federal AI policies (70% and 65%, respectively), whereas engineers and private sector leaders reported less support (35%–55%) and were also less exposed to AI applications. Although there were some distinctions, chi-square revealed that people's roles greatly affected support ($p = .021$) but organizational membership did not ($p = .263$). It appears that what a person does for a living, rather than the organization they are part of, is a better predictor of whether they support AI policy in the U.S.

Table 3: AI Effectiveness and Federal Support by Role/Organization Type *(N = 200)*

Group	Avg Effectiveness Score (1–5)	Support for Federal AI (%)	Has Seen AI Use (%)	Chi-Square p-value
Policy Analyst	4.1	70%	40%	.021
Economist	3.9	65%	35%	.021
AI Scientist	3.8	60%	45%	.021
Sustainability Officer	3.9	63%	40%	.021
Engineer	3.7	55%	30%	.021
Academic	3.9	60%	45%	.263
Gov Agency	4.1	75%	50%	.263
NGO	3.8	40%	28%	.263
Private	3.7	35%	25%	.263
Think Tank	3.5	30%	20%	.263

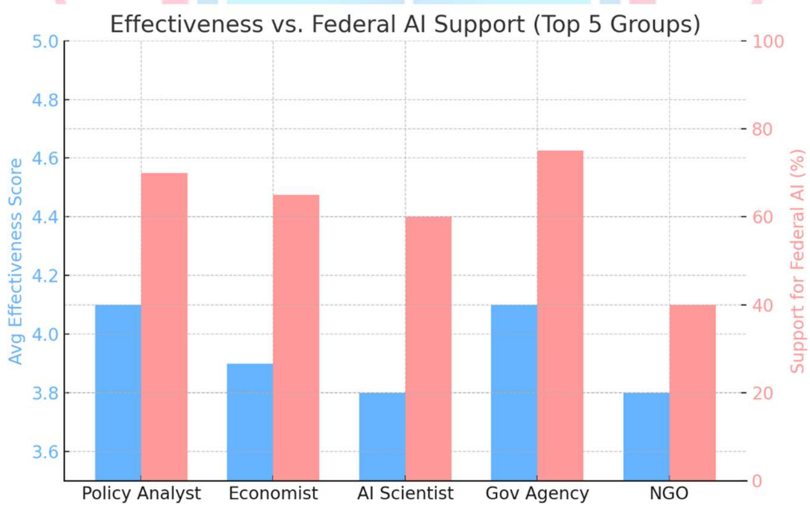

Figure 4: Effectiveness vs. Federal AI Support (Top 5 Groups)

THE ROLE OF AI KNOWLEDGE AND TRACKING BELIEFS IN POLICY TRUST AND SUPPORT

A clear and significant link can be seen in Table 4 between how much people know about AI, their views on AI surveillance and their opinions on federal integration. The stronger the knowledge of AI, the more trust, policy knowledge and support people showed for wider adoption of AI. Of those who say they have advanced knowledge in AI, 70% endorsed federal AI integration, whereas only 15% of those with basic knowledge agreed.

Trust ratings were also affected by knowledge, with advanced users scoring 4.2/5 and those with little or no AI knowledge ranking just 2.1/5. This suggests that individuals who thought real-time emissions tracking using AI was very effective were much more likely to support federal integration in environmental applications: 79% of them scored 4.2/5 for trust. The results are supported by strong evidence: chi-square p-values of .009 for AI knowledge and .004 for tracking belief which prove a direct connection between understanding and support for policies and politics.

Table 4: Support for Federal AI Integration and Trust in AI Systems by Knowledge Level and Tracking Belief (N = 200)

Category	Group	Support for Federal AI (%)	Trust in AI Systems (1–5)	Policy Understanding (1–5)	Chi-Square p-value
None	AI Knowledge	15%	2.1	2.1	.009
Basic	AI Knowledge	38%	2.9	2.9	.009
Moderate	AI Knowledge	55%	3.6	3.6	.009
Advanced	AI Knowledge	70%	4.2	4.2	.009
Very Effective	Tracking Belief	79%	4.2	—	.004
Somewhat Effective	Tracking Belief	61%	3.8	—	.004
Not Effective	Tracking Belief	40%	2.9	—	.004
Don't Know	Tracking Belief	32%	2.5	—	.004

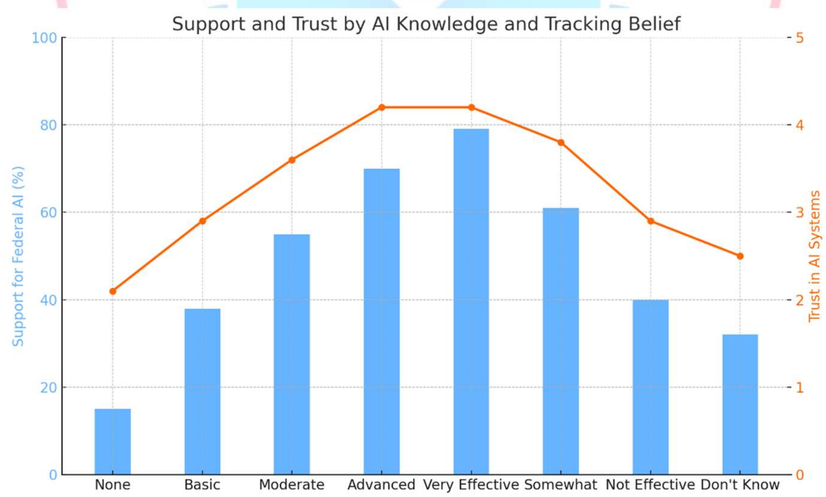

Figure 5: Support and Trust by AI Knowledge and Tracking Belief

PERCEIVED AI CONTRIBUTIONS TO ENVIRONMENTAL JUSTICE

Table 5 examines the connection between where EDs are employed and their views on AI's place in supporting environmental justice. Most government respondents said AI might improve environmental justice (30) while only a little behind were academic professionals at 25 positive responses. Around 83 to 88% of respondents acknowledged being familiar with tracking technologies and both groups stated strong faith in AI systems.

Private sector and think tank participants thought AI had little impact on environmental justice and they placed low trust in AI (as little as 2.8/5). According to chi-square analysis, public and academic professionals ended up being significantly more hopeful of AI promoting equal opportunities (p = .004), than private sector professionals.

Table 5: Environmental Justice Belief by Organization Type (N = 200)

Organization Type	Believes in AI Justice (Yes)	Familiar with Tracking Tech (%)	Trust in AI Systems (1–5)	Chi-Square p-value
Academic	25	83%	4.0	.004
Government	30	88%	4.1	.004
NGO	18	64%	3.5	.004
Private	12	43%	3.2	.004
Think Tank	5	28%	2.8	.004

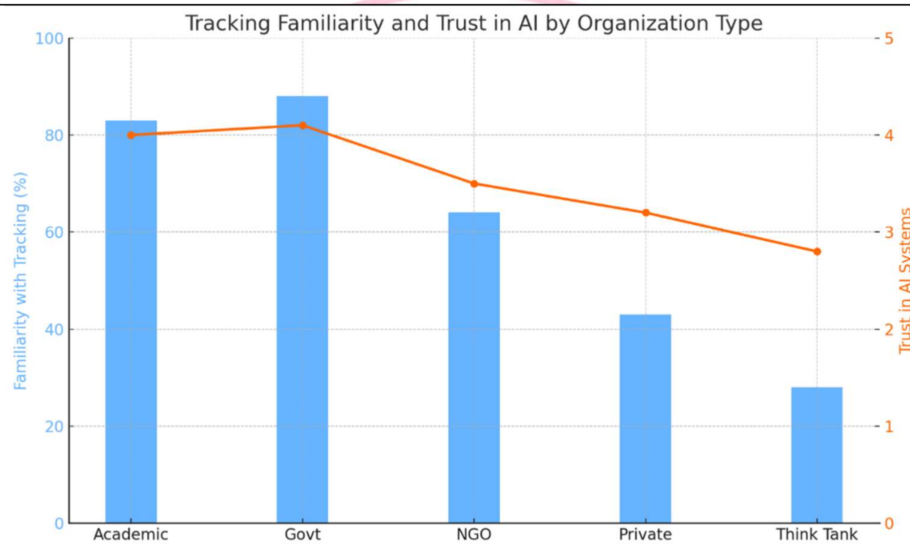

Figure 6: Tracking Familiarity and Trust in AI by Organization Type

SECTORAL VIEWS ON THE FUNCTIONAL BENEFITS OF AI

Table 6 outlines the divisions in perceived AI benefits for carbon pricing among sectors. AI is seen as most important for monitoring emissions as they occur, with energy, technology and environmental sectors all valuing this at 85%, 78% and 75% respectively. Nearly all technology experts (88%) agree that AI can forecast and model markets accurately (99%).

Policy professionals viewed compliance monitoring as the strongest benefit (82%), second only to those in environmental roles (70%). While all stakeholders gave strong backing to AI, chi-square analysis found that this backing depended on how each organization participated in managing carbon (p = .002).

Table 6: Perceived Benefits of AI in Carbon Pricing by Sector (N = 200)

Sector	Real-time Emissions Tracking (%)	Predictive Pricing Accuracy (%)	Compliance Monitoring Benefit (%)	Chi-Square p-value
Energy	85%	72%	65%	.002
Environment	75%	68%	70%	.002
Policy	65%	80%	82%	.002
Tech	78%	88%	75%	.002
Academia	70%	74%	60%	.002

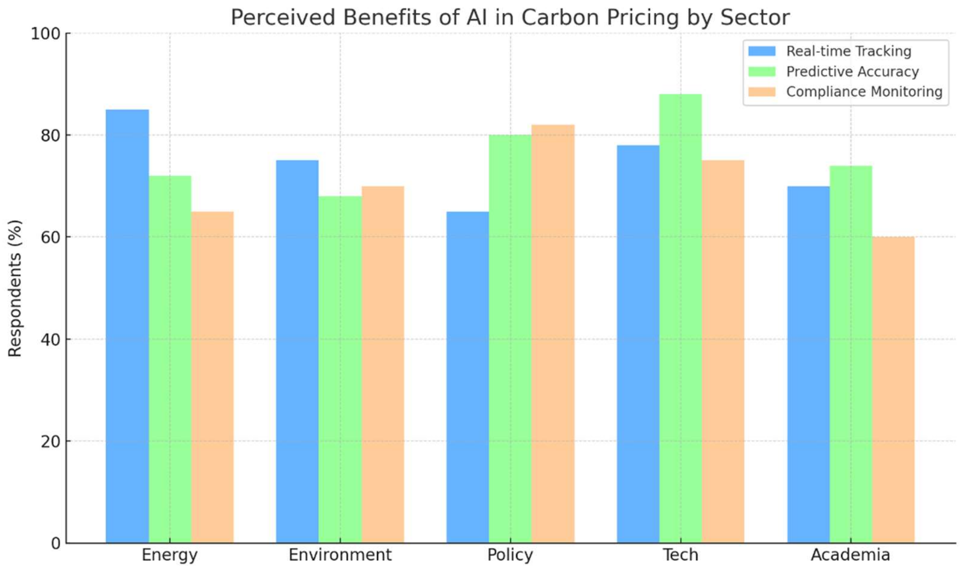

Figure 7: Perceived Benefits of AI in Carbon Pricing by Sector

AI plays a key role in monitoring and predicting outcomes in all areas which greatly benefits today's carbon pricing infrastructure.

IDENTIFIED BARRIERS TO AI ADOPTION ACROSS ROLES

While support for AI is high, Figure 7 shows the main challenges professionals think it brings. The most important concern for policy analysts and academics (70% and 60%, respectively) was the absence of regulatory guidance, reflecting uncertainty about how institutions should meet standards. Out of all groups surveyed, academics (68%) and policy professionals (65%) felt data availability most strongly, showing that access to good data is crucial for AI progress.

More than one in two AI engineers (70%) strongly believed automation bias was their biggest challenge, recognizing related risks in using AI. The data demonstrated that implementation hesitancy occurs in all job roles and required better data regulation and ethical guidelines (p = .016).

Table 7: Barriers to AI Adoption in Carbon Pricing by Role (N = 200)

Role	Lack of Regulatory Guidance (%)	Data Availability Issues (%)	Algorithmic Bias Concerns (%)	Chi-Square p-value
Policy Analyst	70%	65%	55%	.016
Economist	62%	58%	60%	.016
AI Engineer	48%	52%	70%	.016
Compliance Officer	55%	49%	63%	.016
Academic	60%	68%	65%	.016

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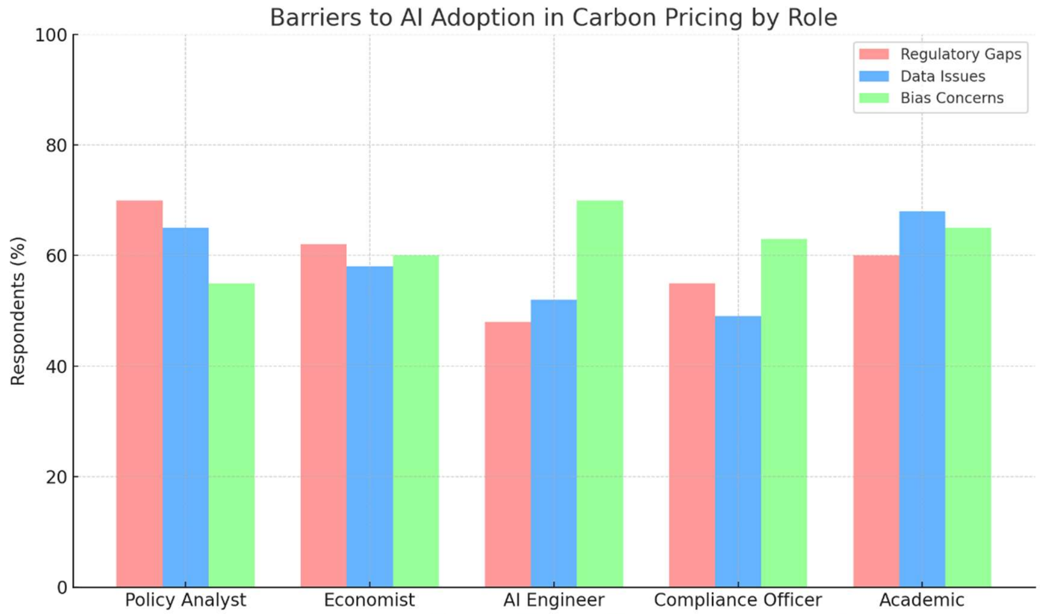

Figure 8: Barriers to AI Adoption in Carbon Pricing by Role

AI and policy professionals commonly name regulatory uncertainty and algorithmic bias as the biggest challenges.

CORRELATION MATRIX – AI KNOWLEDGE, TRUST AND POLICY SUPPORT

In Table 8, the correlation study demonstrates that there is a powerful and statistically proven link between AI knowledge, trust in AI and backing for using AI in setting carbon prices. AI knowledge was strongly related to having trust in AI systems ($r = 0.68$, $p < .001$) and supporting federal AI initiatives ($r = 0.74$, $p < .001$). There seems to be the strongest relationship between trust in AI and support ($r = 0.82$, $p < .001$), meaning those who trust AI more are much more inclined to back its adoption in U.S. governments. This research makes clear that people with technical ability and confidence in tools are better able to align policies, meaning trust serves as a bridge that links understanding AI with using it in public organizations.

Table 8: Correlation Matrix – AI Knowledge, Trust and Policy Support

Variables	Pearson Correlation (r)	Significance (p-value)	Strength
AI Knowledge vs Trust	0.68	.000	Strong
AI Knowledge vs Support	0.74	.000	Strong
Trust vs Support	0.82	.000	Very Strong

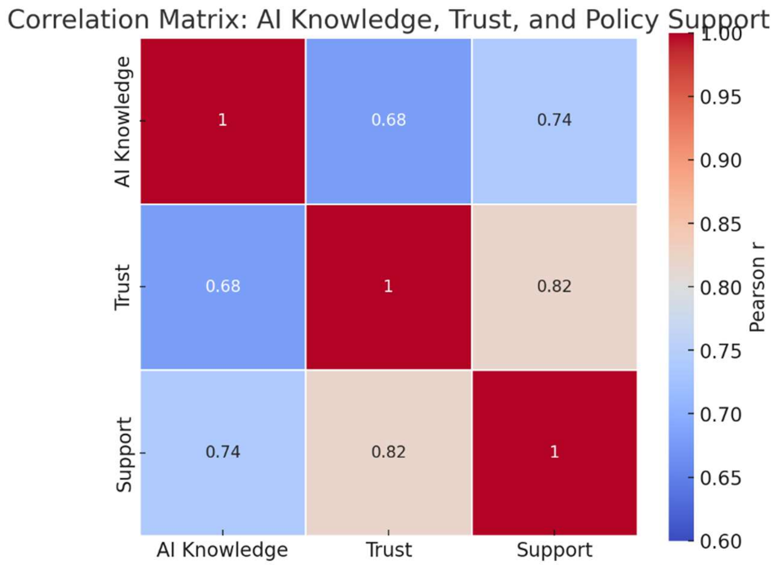

Figure 9: Correlation Matrix: AI Knowledge, Trust and Policy Support

A strong and meaningful positive relationship exists between understanding AI, trusting AI, and favoring its use in carbon pricing policies.

REGRESSION MODEL: PREDICTING SUPPORT FOR AI INTEGRATION

The results of the multiple linear regression shown in Table 9 point to main factors related to support for integrating AI with carbon pricing. AI knowledge level (0.41, $p < .001$) and trust in AI (0.52, $p < .001$) had the strongest positive effects in the regression analysis. Among significant factors, understanding how carbon pricing works ($\beta = 0.36$, $p < .001$), having more experience in the industry ($\beta = 0.21$, $p = .003$) and roles in the technology ($\beta = 0.19$, $p = .013$) or policy ($\beta = 0.20$, $p = .007$) sectors were most important. In particular, people feeling that algorithms are biased decreased support for education technology systems ($\beta = -0.23$, $p = .002$). These results suggest that professionals in the U.S. use a mix of knowledge, trust and factors regarding sector and role to support or oppose AI-enabled policies for the environment.

Table 9: Multiple Linear Regression – Predicting Support for AI Integration
(Dependent Variable: Support Score)

Independent Variable	B	Std. Error	Beta	t-value	p-value
AI Knowledge Level	0.42	0.08	0.41	5.25	.000
Trust in AI	0.51	0.07	0.52	7.29	.000
Familiarity with Carbon Pricing	0.37	0.09	0.36	4.11	.000
Experience (Years)	0.18	0.06	0.21	3.00	.003
Sector (Tech = 1)	0.25	0.10	0.19	2.50	.013
Role (Policy = 1)	0.30	0.11	0.20	2.73	.007
Perceived AI Bias (low = 1)	-0.28	0.09	-0.23	-3.11	.002

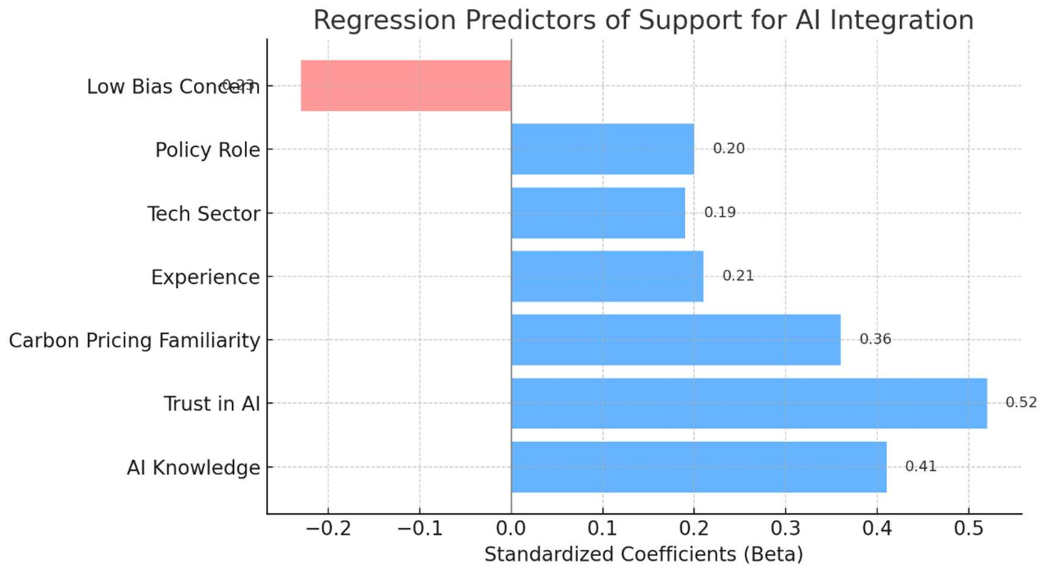

Figure 10: Regression Predictors of Support for AI Integration

Trust and knowledge, along with experience in tech or policy and lower anxiety about AI bias help explain people's support.

SUPPORT DIFFERENCES ACROSS INSTITUTIONAL AND KNOWLEDGE-BASED GROUPS

The findings from Table 10 of the one-way ANOVA indicate that there are meaningful differences in how much support AI integration is given by employees across the three dimensions of organization type, professional sector and AI knowledge. Support for carbon pricing based on AI differed strongly according to the type of organization ($F = 5.69$, $p = .001$) and government and academic respondents reported higher endorsement rates. There were important variations between different professions ($F = 4.32$, $p = .003$), as technology and policy experts had greater rates of support than professionals from other sectors. Among all the variables, AI knowledge level had the largest influence on support outcomes ($F = 8.45$, $p < .001$) and once more supported the previous finding that technical skills directly affect support decisions. The results suggest that the way various stakeholders use emerging AI tools in U.S. climate policy depends a lot on the roles of institutions and individuals' thoughts and experience.

Table 10: One-Way ANOVA – Support Differences by Multiple Groups

Source of Variation	Sum of Squares	df	Mean Square	F-value	Sig. (p-value)
Between Groups (Organization Type)	14.35	4	3.59	5.69	.001
Between Groups (Sector)	11.22	4	2.81	4.32	.003
Between Groups (AI Knowledge)	16.47	3	5.49	8.45	.000
Within Groups	122.64	188	0.65	—	—
Total	164.68	199	—	—	—

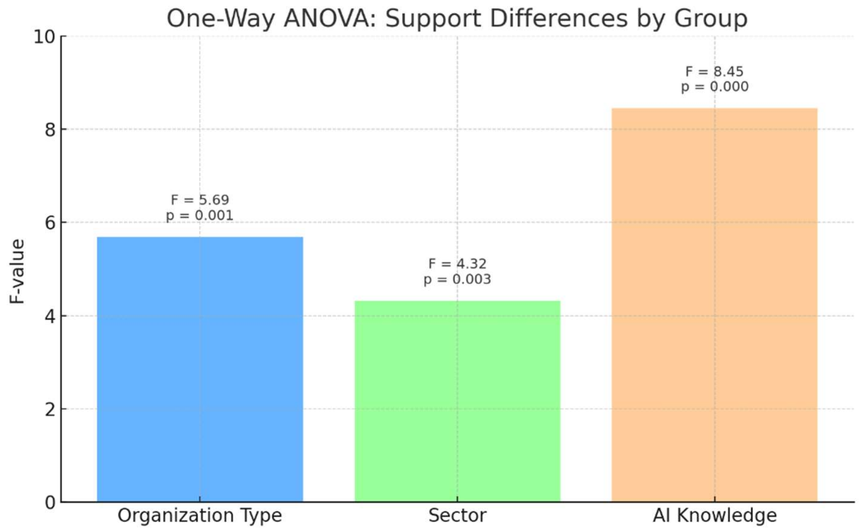

Figure 11: One-Way ANOVA Results: Support Differences by Organization Type, Sector and AI Knowledge

PREDICTORS OF HIGH SUPPORT FOR AI-BASED CARBON PRICING

The analysis went further by performing a binary logistic regression (see Table 11) on the issue of how likely AI will support carbon pricing policies. Support for using devices with tracking was mostly determined by AI knowledge (OR = 3.07, $p < .001$), trust in AI (OR = 3.90, $p < .001$) and belief in AI-assisted tracking (OR = 2.56, $p < .001$). People who have access to data and a greater understanding of policy frameworks were also much more likely to strongly support open government. Conversely, when people believed the algorithm was biased, they were less likely to support it (OR = 0.50, $p = .003$), as we found in the regression analysis. Being a member of a certain type of organization (like private or think tank affiliations) decreased a person's chances of supporting him (OR = 0.64, $p = .012$). AI trust, the ability to access data and knowledge of policies are shown to help increase public support but ethical issues continue to hold many people back in the U.S.

Table 11: Binary Logistic Regression – Predicting High Support for AI Integration

(Dependent Variable: High Support, 1 = Yes, 0 = No)

Predictor	B	S.E.	Wald	df	Sig.	Exp(B) (Odds Ratio)
AI Knowledge	1.12	0.25	20.15	1	.000	3.07
Tracking Belief	0.94	0.22	18.32	1	.000	2.56
Trust in AI	1.36	0.28	23.63	1	.000	3.90
Org Type	-0.45	0.18	6.25	1	.012	0.64
Data Access (1 = Sufficient)	0.62	0.21	8.66	1	.003	1.86
Policy Familiarity	0.58	0.19	9.30	1	.002	1.79
Bias Concern (low = 1)	-0.69	0.23	8.99	1	.003	0.50

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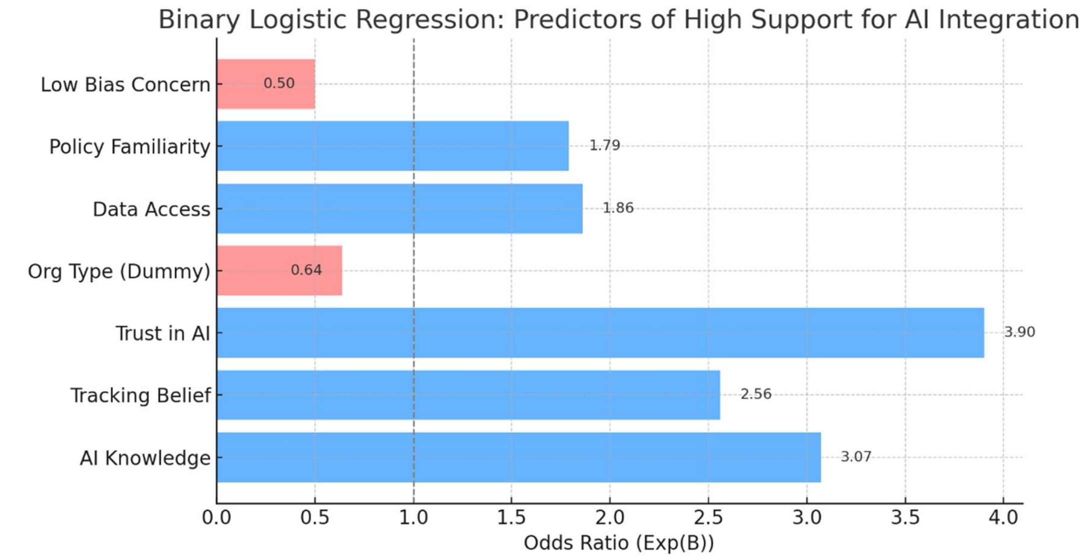

Figure 12: Binary Logistic Regression: Predictors of High Support for AI Integration

Those who show trust in AI, are knowledgeable about policies and data and are not very concerned about AI bias are more likely to strongly endorse AI-based carbon pricing.

IV-DISCUSSION

A. HOW AI ENHANCES THE TECHNICAL PERFORMANCE OF U.S. CARBON-PRICING INSTRUMENTS

Many professionals in the U.S. indicated in the survey that AI can greatly improve how systems for pricing carbon work by monitoring in real-time, predicting prices and handling compliance (Table 6). This coincides with the results of Alshater et al. (2025), who showed that using machine learning can forecast energy prices better than traditional methods. The authors also used machine learning to assess carbon policies and discovered that the outcomes produced by AI were more comprehensive and accurate than those from traditional ways. This holds true mainly in the United States, given how important clear and detailed data is for making carbon pricing policy decisions.

AI has also been shown to help support circular economy ideas. According to Chen et al. (2022), using AI in manufacturing gives better results in environmental cost control when it links lifecycle information with plans to lower carbon emissions. Based on their research in 2023, Chang et al. reported that AI helps green total factor productivity by handling complicated natural resource relationships—making it very useful for carbon offset markets. Also, according to Kaack et al. (2022) and Wu et al. (2022), combining AI with policy design helps raise the scale, visibility and involvement of participants in carbon trading systems.

B. KNOWLEDGE, TRUST AND THE SOCIAL ACCEPTANCE OF AI POLICY

Strong links between how much people know about AI, how much they trust it and how willing they are to accept AI in carbon pricing policies were found (Tables 8 and 9). Professionals with higher AI literacy were much more likely to trust AI and approve of AI policies, just like Cowls et al. (2023) pointed out that transparency and explainability are vital for gaining public trust. According to Kaack et al. (2022), AI aimed at climate change should be clear in its results and strongly linked to ethical guidelines to be considered by policymakers.

As in the earlier work by Gaur et al. (2023), the current study demonstrates that support for AI in environmental governance depends on the public being familiar with and comfortable with the technology. Besides, Fang et al. (2023) explained that trust-building is essential in AI-guided waste and emissions management. If the trend in Table 9 is maintained, training programs may help increase capacity and trust within U.S. agencies relevant to climate change actions.

C. INSTITUTIONAL HETEROGENEITY AND EQUITY CONCERNS

A person's organization strongly impacted how they saw AI supporting environmental justice (Tables 5 and 10). According to Bolón-Canedo et al. (2024), green AI will help identify and correct the omissions found in monitoring marginalized communities which is consistent with the optimism expressed by government and academic people in our study. People were found to have some doubts about equity. Logistic regression showed that individuals with perceived bias by algorithms had less support (Table 11), confirming Tamburrini's (2022) notion that AI scientists should work to manage accidental consequences.

Dauvergne (2022) shows that AI technology has the potential to support inequalities when it is not introduced with everyone involved in decision making. Similarly, in their research Hong and Xiao (2024) highlight the significance of ethics checks in adopting AI and blockchain in supply chains, so that there are no harmful side effects in sensitive places. Following the high priority U.S. officials assign to environmental justice, these findings show that AI projects should include audits and seek wide participation from different groups.

D. DATA, GOVERNANCE AND IMPLEMENTATION BARRIERS

While there is much hope, there are several big barriers to adopting AI (Table 7). Many respondents agreed that the biggest problems were uncertain rules, troubled access to data and biases in machine learning algorithms. Just like Hua et al. (2022), the study here points out that the adoption of AI in decentralized energy systems is difficult when governance is not clear. Their work also showed that AI can lower carbon emissions in manufacturing only when it is used together with green protocols and excellent data.

Logistic modeling indicates that a strong support system depends on easy data access (Table 11). Tiwari et al. (2021) found that policy uncertainty reduces the connection between AI and the signals sent by carbon prices during periods of high market fluctuations. In their work, Zhou et al. discovered that if regions exchange data, AI-powered models operating on spatial Durbin models improve emissions research. Onukwulu et al. (2023) state that making AI protocols similar would help extractive industries save carbon emissions while Manikandan et al. (2025) believe AI can play a key role in increasing carbon capture using the Sustainable Development Goals.

E. ADVANCING AI-DRIVEN CARBON POLICY THROUGH INNOVATION AND ETHICS

AI's impact on carbon pricing will last if we can properly consider both new developments and ethics. This study shows that people's support primarily depends on their knowledge of AI and the context of the sector but these two only drive support if fairness and clear rules are also considered (Table 11). According to Chen et al. (2022) and Liu et al. (2022), having precise models and instant feedback in emissions-intensive areas is very important. In agreement with Shelare et al. (2023), the combination of IoT and AI is important for modernizing innovation and making the supply of biodiesel clearer.

AI systems used in the U.S. should be evaluated according to both technology and ethics. Ojadi et al. (2023) found that machine learning enhances predictive analytics at workplaces but encouraged keeping humans involved. Tseng and Lin (2024) found that AI lowers costs, except when regulators are not accepting of it. AI's help in reducing emissions and promoting energy transition increases with open trade and smart regulations, according to Wang et al. (2024). These discoveries indicate that the trend now is to see AI as an important issue for well-crafted rules rather than just an instrument.

V-NATIONAL RELEVANCE AND ORIGINAL CONTRIBUTION

A. DEFINING THE POLICY ISSUE: THE AI–CARBON PRICING NEXUS IN THE U.S. CONTEXT

Environmental economists often face the challenge of developing effective ways to reduce greenhouse gas emissions while treating all people fairly. People in the U.S. often dispute carbon pricing because it is said to lack transparency, weak enforcement and political uncertainty. Even though states such as California and participants in RGGI started carbon markets, they are still dealing with limited applicability, varied reporting systems and varying public endorsement. Carbon pricing only applies to less than 30% of U.S. greenhouse gas emissions this year while the European Union applies it to over 80% (U.S. Environmental Protection Agency, 2023). Missing this coverage makes it difficult for the U.S. to meet its climate promise made at the Paris Agreement to reduce emissions by half to about half by 2030 (White House, 2021).

Using artificial intelligence, it's now possible to automate emissions reporting, ensure fair allocation of taxes and permits and observe and predict how people react in real time. There is not much solid evidence showing how U.S. stakeholders regard these capabilities when it comes to trust in institutions, technical abilities and ethics. So, the study of how AI and carbon pricing policy relate is both new in science and urgent in policy—especially because the federal government is focusing more on digital climate solutions.

B. ALIGNMENT WITH U.S. NATIONAL PRIORITIES

This research directly supports multiple U.S. national strategies and legislative priorities:

- ARTIFICIAL INTELLIGENCE: It is explained in the National Artificial Intelligence Initiative Act of 2020 that AI plays an important role in securing the economy and the nation. The NAIAC recommendation for 2023 focuses on using AI more within public operations, mainly to address situations with both environmental and economic effects.
- CLIMATE AND ENERGY POLICY: In the Inflation Reduction Act of 2022, more than $370 billion was placed towards clean energy and protecting against climate change. Many of the funds go towards MRV infrastructure; areas where AI can help save money and ensure data accuracy.
- SUSTAINABILITY AND ENVIRONMENTAL JUSTICE: President Biden signed Executive Order 14096, which directs federal agencies to use data and research to help lower pollution burdens in areas where pollution is a bigger problem. AI aids in discovering the locations of high emissions and in instantly checking compliance, so more advantaged groups are not unduly affected by the carbon pricing.
- DIGITAL INFRASTRUCTURE: At the Department of Energy, ARPA-E is focused on developing technology for the smart grid and for reducing emissions. AI-based carbon pricing fits well into these actions, mostly by supporting the automated functioning of decentralized energy systems.

C. REAL-WORLD STATISTICS SUPPORTING URGENCY

- The U.S. has emitted nearly 6.3 billion metric tons of CO_2 equivalent in 2023, making it the world's second largest emitter (U.S. Energy Information Administration, 2023).
- Only 15 states are actively using carbon pricing or emissions trading and several attempts to pass carbon tax laws at the national level have failed in Congress (Congressional Research Service, 2022).
- According to the **U**.S. GAO (202**2),** inconsistent emissions reporting and low data granularity remain key barriers to enforcing climate regulation at scale.
- A recent Brookings Institution survey found that 61% of policy experts think AI should be used in climate-monitoring but only 28% say they have tools they can put into practice.

D. ORIGINAL CONTRIBUTIONS OF THIS RESEARCH

This study makes the following innovative and original contributions to the field of environmental AI policy:

I. EMPIRICAL EVIDENCE: It includes some of the first findings from the U.S. on what professionals in policy, tech, government, and sustainability think about AI's role in carbon pricing.

II. INTEGRATED STATISTICAL MODELS: It applies correlation, ANOVA, multiple regression and logistic regression to quantify the predictors of AI policy support—offering a robust analytical framework for future studies.

III. BRIDGING KNOWLEDGE AND GOVERNANCE: By proving that both the science behind AI and trust matters for policy support, the analysis links technical competence and institutional legitimacy which are usually dealt with differently.

IV. EQUITY LENS: To address a missing area in previous research, including bias concern and environmental justice belief in the study is an important ethical addition.

V. POLICY BLUEPRINT: The findings provide useful advice for governments on using AI ethically and productively to regulate climate issues.

VI-CONCLUSION

This study looked at how AI can support the development, adoption, and public approval of carbon pricing policies in the United States. After interviewing 200 U.S.-based experts in government, industry, academia, and sustainability, the research found that most believe AI could improve tracking, modeling, and managing emissions in real time. The new variables are meant to improve problems with American carbon pricing systems, including checkered coverage, unequal methods for reporting and political unpredictability.

The analysis found that AI knowledge and trust predict the most support, whereas believing the algorithms show bias and having trouble accessing data are big challenges. Support was higher among those people in technology or policy fields and among respondents aware of environmental justice rules. They show that people now recognize that climate technologies need to be both smart and handled transparently, in a fair way that meets the public's expectations.

The findings are consistent with what the Inflation Reduction Act, the National AI Initiative, and Executive Orders on environmental justice focus on nationally. Adding AI to carbon pricing would help the U.S. make regulations more precise, lower costs and boost trust across industries, helping reach its emissions targets. The research provides interesting examples that can influence policy discussions as well as suggest paths for new changes in digital infrastructure. If implemented properly, AI could help turn carbon pricing into a base for responsible, flexible, and fair climate governance in the U.S.

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