International Journal of Recent Innovations in Academic Research

E-ISSN: 2635-3040; P-ISSN: 2659-1561
Homepage: https://www.ijriar.com/
Volume-9, Issue-4, October-December-2025: 354-360

Research Article

An Evaluation of AI Preparedness Index and Carbon Offset from a Social Capital Perspective

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Received: November 19, 2025 **Accepted:** December 10, 2025 **Published:** December 17, 2025

Abstract
Multiple Linear Regression, Principal Component Analysis, and Gradient Boost Regression are used to investigate both the effectiveness of carbon offset programs and the threat posed by AI technologies, using datasets from 71 countries. The common outcome of these three models is that the carbon offset program is not practical, on the one hand, and that the threats related to AI technologies are not clearly observed, on the other hand. To the contrary, the Artificial Intelligence Preparedness Index (AIPI) moves closely with the Social Capital Index (SCI), suggesting that AI technologies can be a long-term factor in sustainability. Although these results are strictly limited to the variable selection and available data sets in this study, AIPI is positively correlated with monthly median wages and negatively correlated with income inequality, implying that the prevalent threat posed by the development of AI technologies is not evident in the data sets used in this study. Widespread fears about AI technologies may become reality in the future, but they are not traceable in current data.
Keywords: AI Preparedness Index, Carbon Offset, Social Capital Index, Income Inequality.

1. Introduction

AI technologies and greenhouse gas emissions have a dual relationship: current AI systems significantly increase electricity demand and associated emissions, but AI is also a powerful tool for reducing emissions across energy, industry, and transportation systems. AI technologies are becoming deeply embedded across the carbon offset market's value chain, from project design and monitoring to trading, pricing, and integrity assurance. This relationship is mutually reinforcing. AI helps solve core credibility and efficiency problems in carbon markets, while growing offset demand creates a business and data infrastructure for more advanced AI tools. This relationship between AI technologies and carbon offset markets is also intertwined with various socio-economic conditions, including economic growth, economic development, changes in the labor share, and the long-term sustainability of economies. With these complicated relationships in mind, this study tries to figure out the associations between the features such as:

(1) Artificial intelligence preparedness index (AIPI);
(2) Social capital index (SCI);
(3) Median monthly wage;
(4) Income inequality;
(5) Labor share;
(6) The amount of CO_2 emissions;
(7) Stock transaction volume measured by the percentage of GDP;
(8) The number of carbon offset projects.

Stock transaction volume is selected to represent a country's level of financial development. Among various possibilities, the sanitation levels are used as proxies for socio-economic development.

2. Literature Review

Carbon offset markets allow emitters to meet climate targets by financing emissions reductions or removals elsewhere, rather than cutting their own emissions, typically via project-based credits in forestry, land use, and energy [1, 2]. Inequities arise because wealthier actors effectively purchase the right to continue emitting [3, 4]. The writer and environmentalist George Monbiot famously compared carbon offsetting to the sale of medieval Catholic indulgences, where the rich could buy themselves out of sin [5]. Simultaneously, the rapid pace of AI technology raises various socio-economic problems and climate concerns stemming from CO_2 emissions supporting this technological revolution. Confronting the job destructions or income inequalities accelerated by AI technologies, Universal Basic Income (UBI) and data dividends are increasingly proposed as policy solutions to address technical inequality, aiming to redistribute economic benefits and mitigate the risks of job displacement and wealth inequality [6, 7, 8].

UBI provides regular, unconditional cash payments to all citizens to achieve income security and reduce poverty [9]. Studies find that UBI can significantly decrease income inequality, mainly if financed progressively [7, 10]. However, the effectiveness of UBI depends on the scope of payments and the fiscal mechanisms used to fund it [7, 11]. A data dividend is a scheme that allows individuals a share of the value generated from their personal data, monetized by large technology companies [10, 12]. Data dividends are invented to address the growing "data divide" and "digital wealth divide" [13]. Careful design, financing, and integration with broader socio-economic policies can be crucial to the success of these policy suggestions [6, 9, 12].

Intuitively, it seems that automation and AI are replacing many jobs, leaving many people unemployed across various fields. That is, trade-offs can exist between the benefits automation and AI bring to our daily lives and risks of job destruction, income inequality, attack on social cohesion, and the decoupling of wages and labor. But before evaluating the legitimacy of UBI and the data dividend, a more rigorous statistical inspection is a prerequisite to pin down the stance on automation and the digital economy stemming from AI regarding sustainable growth and income inequality.

3. Data Analysis

To simultaneously assess the efficacy of the carbon offset market and the socio-economic implications of AI technologies, datasets are drawn from various sources, including the World Bank, the World Inequality Index, the OECD, and the IMF. The number of countries is reduced to 71 due to the availability of suitable data sets. The variables selected to inspect the role of AI are Artificial Intelligence Preparedness Index (AIPI, 2022), Social Capital Index (SCI, 2024), change of nominal GDP from 2010 to 2024, change of labor share in GDP from 2010 to 2020, stock transaction volume as a percent of GDP in 2023, income inequality in 2024, and median monthly wage of 2023. Data on carbon offset projects were retrieved from the Voluntary Registry Offsets Database (UC Berkley). Data on CO_2 emissions were obtained from EDGAR (European Commission, 2025). Income inequality and real GDP data were retrieved from the World Inequality Database (WID). Sanitation rates and stock transaction volumes were retrieved from the World Development Indicators (World Bank).[1]

3.1. PCA

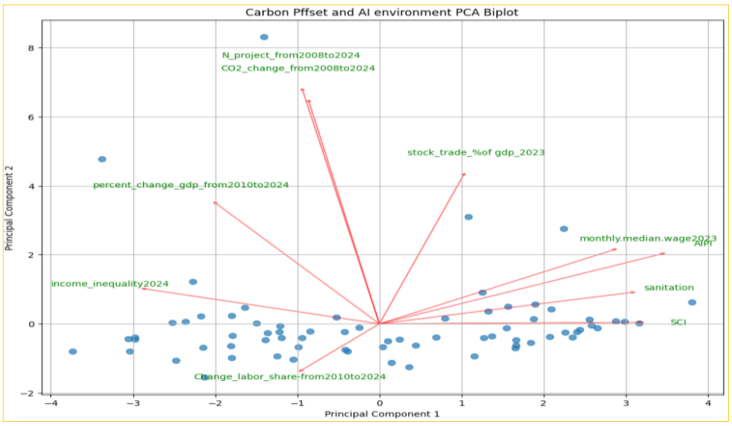

Figure 1. Carbon offset PCA biplot.

[1]**Source of Data Links:**
https://gspp.berkeley.edu/berkeley-carbon-trading-project/offsets-database
https://edgar.jrc.ec.europa.eu/report_2025
https://wid.world/data/
https://datacatalog.worldbank.org/search/dataset/0037712/world-development-indicators

The relationships among the variables-including the number of carbon offset projects, real GDP, income inequality, socio-economic development measured by sanitation rate, and financial status measured by stock transaction volume-are shown in the PCA biplot in Figure 1. The number of carbon offset projects is cumulative from 2008 to 2024, and the change in CO_2 emissions is from 2008 to 2024.

Table 1. Factor loadings of principal component analysis.

Variable	**Principal component 1**	**Principal component 2**
Income inequality in 2024	-0.74844057	0.1215101
Stock trade (% of GDP) in 2023	0.26903002	0.51882198
Number of projects from 2008 to 2024	-0.24565164	0.81442829
Sanitation in 2024	0.80538983	0.10934071
Change in CO_2 emissions from 2008 to 2024	-0.22516576	0.77428777
AIPI 2022	0.90171443	0.24358515
SCI 2024	0.83046602	0.00530005
Change in labor share 2010-2024	-0.24869645	-0.1613961
Percent change in GDP from 2010 to 2024	-0.52287158	0.41996603
Monthly median wage 2023	0.74843508	0.25802525

The PCA biplot below and the factor loadings in Table 1 demonstrate several aspects:

1) The number of carbon offset projects and the change in CO_2 emissions are almost perfectly correlated, suggesting that the effect of the carbon offset program can be ineffective.
2) The monthly median wages are positively correlated with AIPI, SCI, and sanitation level, while they are negatively correlated with income inequality. All these four features contribute to the first principal component.
3) The number of projects and CO_2 emissions contribute to the second principal component, both of which are positively correlated with stock trade measured by percent of GDP and the percent change of GDP.
4) Both AIPI and SCI are negatively correlated with income inequality.

3.2. Multiple Linear Regression

Based on the correlation structures recognized by the PCA biplot, several multiple linear regression models with different dependent variables are applied. Only the equations with adjusted R^2 greater than 0.5 are reported as equations from 1 to 4.

$$Inequality_{2024} = 0.827_{(0.043)} + 1.220\cdot 10^{-4}{}_{(7.164\cdot 10^{-5})}\cdot Stock\_trade_{2023} - 0.009_{(8.770*10^{-4})}\cdot SCI_{2024} + 0.003_{(0.001)}\cdot \Delta Labor\ Share \quad \text{with adjusted } R^2 = 0.624 \qquad (1)$$

$$SCI_{2024} = 52.151_{(5.216)} - 45.733_{(8.0681)}\cdot Inequality_{2024} - 0.004_{(0.002)}\cdot N\ of\ Project + 0.001_{(8.268\cdot 10^{-4})}\cdot \Delta CO_2 + 25.859_{(4.989)}\cdot AIPI_{2022} \quad \text{with adjusted } R^2 = 0.707 \qquad (2)$$

$$AIPI_{2022} = 0.150_{(0.044)} + 3.406\cdot 10^{-5}{}_{(1.997\cdot 10^{-5})}\cdot N\ of\ Project + 0.002_{(3.193\cdot 10^{-4})}\cdot Sanitation + 0.005_{(0.001)}\cdot SCI + 2.475\cdot 10^{-5}{}_{(4.390\cdot 10^{-6})} Median\ Wage_{2023} \quad \text{with adjusted } R^2 = 0.805 \qquad (3)$$

$$Median\ Wage_{2023} = -4155.720_{(720.260)} + 11367.053_{(1201.001)}\cdot AIPI_{2022} \quad \text{with adjusted } R^2 = 0.559 \qquad (4)$$

As expected, AIPI and SCI are mutually significant variables, implying that the AI development level measured by AIPI can be a long-term sustainable growth factor measured by SCI. At least within the features selected in this study, AI-related income inequality is not present. The number of carbon offset programs is positively associated with AIPI and negatively with SCI. To compensate for the limitations of nonlinearity among the variables, Gradient Boost Regression is added, albeit at the cost of some interpretability.

3.3. Feature Importance

Feature importance in gradient boost regression, commonly calculated based on the reduction in the loss function, refers to how much each input variable contributes to the model's predictions. Features with higher importance scores have a greater influence on the model's output, meaning they are used more frequently and more effectively in splits that improve prediction accuracy.

Table 2. Feature importance of gradient boost regression.

Dependent/ Independent	Income inequality		SCI		AIPI		Median wage
SCI	0.6099	Income inequality	0.6095	ΔCO_2	0.6023	AIPI	0.6322
Stock trade	0.1361	AIPI	0.1447	Median wage	0.1882	ΔGDP	0.1192
ΔGDP	0.0869	ΔCO_2	0.0777	Sanitation	0.1367	ΔCO_2	0.0857
AIPI	0.0629	Number of projects	0.0659	Income inequality	0.0308	Number of projects	0.0683
ΔLabor share	0.0514	ΔLabor share	0.0420	ΔGDP	0.0213	Stock trade	0.0357
Number of projects	0.0269	Stock trade	0.0254	SCI	0.0085	Sanitation	0.0261
Sanitation	0.0145	Sanitation	0.0133	Stock trade	0.0073	Income inequality	0.0191
Median wage	0.0067	Median wage	0.0113	ΔLabor share	0.0041	SCI	0.0124
ΔCO_2	0.0048	ΔGDP	0.0102	Number of projects	0.0008	ΔLabor share	0.0013

Table 2 summarizes the feature importance of explanatory variables when different dependent variables are selected in Gradient Boost Regression. The variables that have the highest feature importance rankings are highlighted. To predict income inequality, SCI is a key variable and vice versa. The change in CO_2 emissions is the crucial factor for explaining AIPI.

In turn, AIPI is an essential factor for tracking the median monthly wages. The threats posed by the burst of AI technologies, such as job destruction or income inequality, are not explicitly captured by the interplay of these 10 variables. Moreover, the remarkable effects of the carbon offset programs on income inequality, median monthly wages, SCI, and AIPI are not present in this table, which is somewhat inconsistent with the results of multiple linear regression models.

3.4. Partial Dependence Plot (PDP)

A partial dependence plot visualizes the marginal effect of features on the predicted outcome, holding all other features constant. It shows how the model's prediction changes, on average, as the value of the selected feature varies across its range.

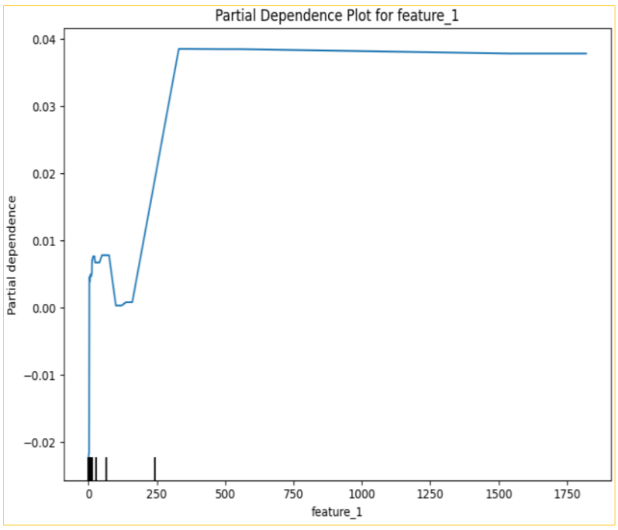

Figure 2. PDP of SCI on income inequality.

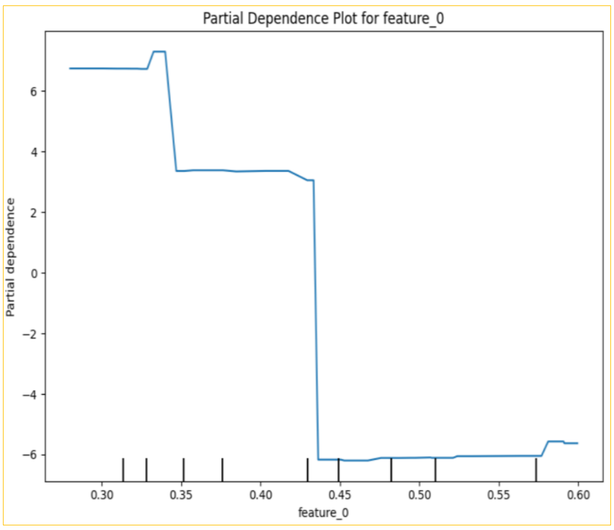

Figure 3. PDP of income inequality on SCI.

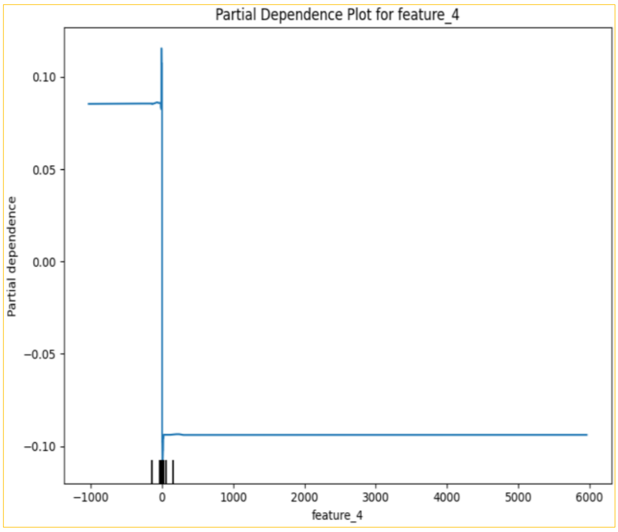

Figure 4. PDP of change in CO_2 on AIPI.

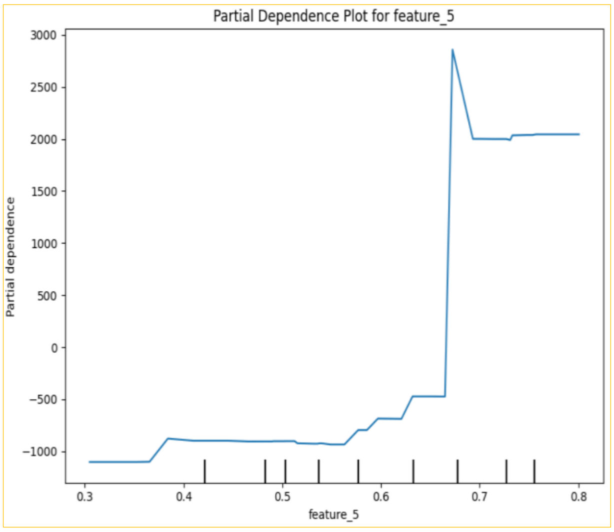

Figure 5. PDP of AIPI on median wage.

Figures 2 to 5 reveal complex non-linearity among the variables. According to Figure 1, when SCI is below the threshold level of about 300, it is positively or negatively associated with income inequality. On the other hand, as income inequality rises, SCI decreases in a stepwise manner. Figure 4 is hard to interpret. Basically, the horizontal portion in a PDP suggests that, on average, changing the feature's value does not affect the model's predictions, implying that the CO_2 change is not essential for the predictions or that its effect is canceled out when averaging across other features. The threshold level is zero, which implies that whether CO_2 emissions increased or not matters. Given that the feature importance is 0.6023, the highest ranking in predicting AIPI, this split around zero is crucial. However, this PDP approach can be misleading when considering the associations among 10 features, since PDP assumes that features are independent.

4. Conclusion

Consequentialism is the philosophical base of the carbon offset schemes [5]. Emission in one place is compensated by absorption in other areas, resulting in net zero [14]. Data sets provide insufficient evidence that carbon offset markets are environmentally and economically effective, except for the association with the stock transaction volumes. Most of all, with a remarkable increase in the number of carbon offset projects, global CO_2 emissions have risen by about 21.9% from 2008 to 2024. Recent studies and policy debates focus on redesigning carbon markets and related instruments to align climate goals with equity and development priorities [2, 4]. Proposed directions include tightening quality rules, [1, 15] embedding justice criteria [2-4], and empowering host countries and communities [16, 17].

However, based on the PCA and Gradient Boost Regression results, carbon offset programs should not be redesigned but instead discarded. They do not enhance income equality, nominal GDP, or the development of social infrastructure. Instead, they are primarily associated with the stock transaction volume measured as a percentage of GDP. The period from 2023 to 2025 marks a clear turning point in voluntary carbon markets, as there was a sharp decline in offset transactions and major actors like Google withdrew from the market. Among the three proposed approaches to redesigning offset systems, tightening quality rules is pivotal, as it is the only measure that could produce a clear negative correlation between CO_2 emissions and the number of offset projects-an essential condition for maintaining the offset framework. On the other hand, the prevailing threat posed by the burst of AI technologies is not evident across the 10 features analyzed in this study. Moreover, AI can serve as a form of social capital that supports long-term sustainability, given the strong positive association between AIPI and SCI in all three statistical approaches, within the limitations of variable selection in this study.

Declarations

Acknowledgments: The authors are thankful to the entire staff of Seoul Innovations Research Institute for insightful ideas and invaluable proofreading.

Author Contributions: YC: Design of study, definition of intellectual content, review manuscript, data collection, prepared first draft of manuscript, data analysis, statistical analysis; IC: Design of study, statistical interpretation, prepared first draft of manuscript, reviewed manuscript; BN: Statistical interpretation, review manuscript, editing.

Conflict of Interest: The authors declare no conflict of interest.

Consent to Publish: The authors agree to publish the paper in International Journal of Recent Innovations in Academic Research.
Data Availability Statement: The datasets generated and/or analyzed during this study are not publicly available but are available from the corresponding author upon reasonable request.
Funding: This research received no external funding
Institutional Review Board Statement: Not applicable.
Informed Consent Statement: Not applicable.
Research Content: The research content of this manuscript is original and has not been published elsewhere.

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Citation: Yoonshik Cho, Inshik Cho and Bob Nam. 2025. An Evaluation of AI Preparedness Index and Carbon Offset from a Social Capital Perspective. International Journal of Recent Innovations in Academic Research, 9(4): 354-360.