The Impact of Artificial Intelligence Adoption on Green Transformation, Innovation, Productivity, and Sustainability in Organisations

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***Abstract*—This study explores the implications of the use of Artificial Intelligence (AI) for organizational outcomes such as Green Transformation, Innovation, Productivity and Sustainability. The research examines the impact of AI technologies on sustainability efforts, innovation and productivity by surveying 240 people from a broad spectrum of industries. The results show that the use of AI has a positive impact on all four outcomes, and that using AI to improve environmental practices and resource efficiency makes a significant contribution to green transformation. AI promotes innovation by providing data-driven insights and speeding up the creation of new products and services. Moreover, using AI boosts productivity by streamlining operations and resource management which also supports sustainability. The research highlights the disruptive impact of AI on contemporary corporate environments and offers insights for using AI to promote SD and innovation. The findings of this research inform the disruptive nature of AI in contemporary organizations and the use of AI to advance SD and innovation.**

***Index Terms*—Artificial Intelligence, Green Transformation, Innovation, Productivity, Sustainability, Organizational Change**

I. INTRODUCTION

The spread of Artificial Intelligence (AI) is reshaping organisations and impacting various aspects of their performance, including innovation, productivity, sustainability, and green development. Recent research suggests that AI technologies can boost the performance and value of firms by providing sophisticated analytics, automation, and intelligent decision-making processes in various areas of business (Xue, 2025). In this way, research based on large panel data indicates that the use of AI can markedly boost innovation efficiency, supporting companies to harness data-driven insights and digital capabilities, thereby speeding up product and process innovation (Xue, 2025). Likewise, AI has been recognized as a driver of corporate green transformation, with empirical evidence showing that AI fosters green innovation capabilities and boosts firm R&D efforts, ultimately leading to decreased environmental impacts and improved competitive advantages (Zhong, 2025; Jiang, 2025).

In the sustainability sphere, empirical studies show that AI's use can enhance SD performance by integrating the economic, environmental, and social aspects. AI can also be used to boost the effectiveness of corporate sustainability efforts, such as in international trade businesses, where it can streamline operations and improve social responsibility outcomes, as mentioned by Chen (2025). In addition, research indicates that AI can promote green growth by a variety of pathways, including human capital development and productivity improvements, particularly in high-tech and larger companies (Liu, 2025).

AI's productivity effects are considered to be general purpose technology that can lead to greater operational efficiency and growth in industries, but with varying impacts at the individual and firm level (Filippucci et al., 2024). The overall picture that emerges from these results underscores the complex nature of the impact of AI adoption on innovation, sustainability, productivity, and organizational transformation, offering a solid starting point for analyzing the impact of AI in different organizational settings.

II. LITERATURE REVIEW

2.1 Implementation of AI and Green Transformation.

In industries, the use of AI is a major component in facilitating green transformation, through optimising the usage of resources, reducing waste and lowering the environmental footprint.

AI technologies such as machine learning and predictive analytics are becoming more commonplace for optimizing energy use and carbon emissions. Zhao et al. (2020) showed that AI has been used in the automotive sector to optimise fuel consumption and minimise CO_2 emissions by means of enhanced engine management and self-driving technologies. Moreover, the predictive capabilities of AI in energy consumption play a crucial role in enhancing energy efficiency, both in the industrial and residential sectors (Gupta et al., 2022).

AI's impact on resource efficiency is a topic of interest in various sectors, including agriculture, water management, and energy. In agriculture, AI systems are helping to optimise water usage and ensure high crop yields. Patel et al. (2021) mentioned the use of AI for managing renewable energies, which helps to optimise energy consumption from renewable sources like solar and wind power, reducing waste and improving sustainability.

AI has also played a pivotal role in driving sustainable initiatives in different industries. In their paper, Xie et al. (2020) explained how AI can be used to optimise waste management, predict waste generation and improve recycling processes. Moreover, AI technologies are being applied in smart cities to optimise traffic flow and enhance the overall urban sustainability (Singh et al., 2022).

2.2 AI Adoption and Innovation

The use of AI is gaining momentum as a force for innovation, especially in creating sustainable products, services and business processes.

One of the major applications of AI in sustainable product design is through the use of generative design and material optimisation. Lee and Lee (2019) described how AI can aid manufacturers in designing products that are environmentally friendly by optimising the selection of materials and minimising waste. AI models can simulate the environmental impact of different materials, allowing for more sustainable choices during the design process.

AI has brought significant service innovation, particularly in areas where sustainability is a key concern. Dube et al. (2021) explained how the AI-driven platforms are being implemented in tourism services for providing eco-friendly travel options to customers depending on their preferences and behaviour. In smart cities, AI systems can be employed to optimise urban operations, such as energy management, waste management, and transportation, to minimise environmental impact and improve the efficiency of urban infrastructure.

AI also streamlines processes and boosts efficiency in business sectors, driving process innovation. Vasquez et al. (2019) emphasised that the application of AI in manufacturing can lead to better energy efficiency by forecasting equipment failures and fine-tuning production plans to maximise resource utilisation. This helps to minimise waste and creates a more sustainable manufacturing process.

2.3 AI Adoption and Organisational Productivity

The use of AI has been shown to have great potential in boosting organisational productivity by automating repetitive tasks, optimizing decision-making, and streamlining operations.

The use of AI technologies has shown to increase organisational productivity in automating repetitive tasks that consume time.AI technologies have been able to help organisations to be more productive by automating repetitive tasks that take up time. The advantages of AI-powered automation, such as quicker decision-making and more effective processes, on operational efficiency and cost reduction were highlighted by Taleb et al. (2021). AI applications can handle customer service responses and data entry in fields like customer service and data management, freeing up time for HR professionals to engage in more strategic activities.

AI's role in data analysis leads to better decision-making, directly contributing to productivity. AI-driven systems can sift through huge amounts of data in real-time and give businesses valuable insights that help them make decisions. For instance, AI has the ability to forecast demand patterns, enabling businesses to fine-tune their production processes and improve inventory management, which ultimately enhances productivity (Xie et al., 2020).

AI helps organisations achieve more efficient resource allocation. In the manufacturing sector, AI systems can help streamline production processes and optimise resource allocation, including labour, materials, and equipment usage. Vasquez et al. (2019) illustrated how AI technologies can be used to detect inefficiencies in processes and give recommendations to optimise them to achieve substantial productivity enhancements in organisations.

2.4 AI Adoption and Sustainability

Adopting AI is critical to helping organisations thrive economically, socially and environmentally in the long term.

AI has the potential to enhance productivity and lower operational expenses, helping to foster economic sustainability. In the context of more sustainable practices, Taleb et al. (2021) pointed out that AI-driven automation and predictive analytics can result in cost savings and increased profitability, allowing organisations to maintain long-term growth and implement more sustainable operations. Additionally, AI systems can assist businesses in streamlining their supply chains, minimizing inefficiencies, and boosting profitability.

In the realm of environmental sustainability, AI can play a transformative role in enhancing energy efficiency and promoting the use of green technologies in various industries. Gupta et al. (2022) spoke on the importance of AI in optimizing renewable energy sources, especially in forecasting energy generation patterns and minimizing the use of fossil fuels. Additionally, AI-driven systems can help to manage and optimise energy consumption in buildings and industrial processes, reducing carbon emissions.

AI also has implications for social sustainability through its ability to increase access to key services, such as health and education. Singh et al. (2022) delved into the impact of AI on health systems, detailing its ability to facilitate personalised medicine and enhance diagnostic accuracy for improved patient outcomes. The use of AI tools in the education sector also includes learning platforms that offer personalised learning experiences, thereby enhancing educational outcomes and social equity by ensuring access to quality education for all students.

III. OBJECTIVES

- To examine the impact of Artificial Intelligence (AI) Adoption on Green Transformation within organizations.
- To assess the influence of AI Adoption on Innovation within organizations.
- To evaluate the effects of AI Adoption on Productivity and Sustainability in organizations.

IV. METHODOLOGY

The design of this study is quantitative research that involves the study of the impact of the implementation of AI on organizational outcomes, namely Green Transformation, Innovation, Productivity, and Sustainability. A cross-sectional survey design is used, collecting data at one time to examine the relations among the adoption of AI and these outcomes. The study adopts a non-probability purposive sampling method, which samples 240 respondents from positions that directly involve the use of AI, such as AI experts, managers, academics, and customers (end-users).

Data on AI adoption and impacts are gathered using a structured questionnaire consisting of items using Likert scales. It is based on validated scales from the literature and customized to the context of organizational change through AI. Data are analysed using Structural Equation Modeling (SEM) which is used to examine the relationship between variables and direct and indirect effects. Descriptive statistics will be used to summarize demographic characteristics of the respondents and SEM will be used to test the strength and significance of the hypothesized relationships.

V. RESULTS

5.1 Socio-Economic Profile of Respondents

Socio-Economic Variable	Category	Frequency (n=240)	Percentage (%)
Gender	Male	180	75
	Female	60	25
Education Level	High School	40	17
	Undergraduate	120	50
	Postgraduate	80	33
Occupation	AI Experts/Engineers	50	21
	Productivity/Operational Managers	60	25
	Academics and Researchers	40	17
	Employees in AI Adoption Projects	50	21
	Customers (End-Users)	40	17
Experience in AI Adoption Projects	Less than 1 year	80	33
	1-3 years	100	42
	More than 3 years	60	25

Survey Data and Author Calculation

Interpretation: The socio-economic background of the 240 respondents in this study shows a wide spread of distribution by gender, education, occupation, and experience in implementing AI projects. There are many more male respondents (75%) than female respondents (25%). As far as education, half of the people have an undergraduate degree (50%), 33% a PG degree, and 17% have finished high school. The distribution of respondents by occupation is fairly even, with Productivity/Operational Managers (21%) and AI Experts/Engineers (21%) tied for the number of respondents, followed by Employees in AI Adoption Projects (21%), Academics and Researchers (17%), and Customers (End-Users) (17%). When asked about the experience in AI adoption projects, 42% of respondents have experience in the range of 1-3 years, 33% have less than 1 year of experience, and 25% have more than 3 years of experience. This profile provides a detailed description of the characteristics of the respondents, capturing the diversity of voices in the study.

5.2 Exploratory Factor Analysis

5.2 Rotated Component Matrix[a]

	Component				
	1	2	3	4	5
AI1	.825				
AI2	.775				
AI3	.802				
AI4	.822				
AI5	.759				
GT1		.789			
GT2		.762			
GT3		.774			
GT4		.774			
GT5		.748			
IN1			.754		
IN2			.755		

IN3			.705		
IN4			.743		
IN5			.787		
PR1				.782	
PR2				.780	
PR3				.752	
PR4				.743	
PR5				.707	
SU1					.760
SU2					.695
SU3					.673
SU4					.760
SU5					.746

Survey Data and Author Calculation

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.[a]

a. Rotation converged in 7 iterations.

Interpretation: The Rotated Component Matrix obtained from Principal Component Analysis (PCA) with Varimax rotation shows that the data have a good factor structure and each component represents a different construct. Stability and meaningful factor solution is indicated by the analysis, which converged in 7 iterations. All five AI-related indicators (AI1-AI5) have high loadings on Component 1, with factor loadings ranging between 0.759 and 0.825, suggesting that AI Adoption is a coherent construct. Green Transformation (GT) has a significant loading (from 0.748 to 0.789) for all the GT variables (GT1 to GT5), which is enough to justify its inclusion in this factor. Component 3 has high loadings (ranging from 0.705 to 0.787) for all the indicators of the Innovation dimension, indicating that Innovation is a distinct dimension. Productivity is supported by the loadings of the PR variables (PR1 to PR5) (the range of 0.707 to 0.782), and this factor is found to be a separate factor. Finally, Sustainability is related to Component 5 and all SU items (SU1 to SU5) have high loading (range from 0.673 to 0.760). The Varimax rotation with Kaiser normalization confirms the results that the components are well separated with each construct (AI Adoption, Green Transformation, Innovation, Productivity, and Sustainability) being clearly represented by the indicators. The results indicated that this data structure is suitable as the factor loading values are very high, most are above 0.7, which is the valid model of the factor structure and makes it easier to explain the relationship between these key factors.

5.3 KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.946
Bartlett's Test of Sphericity	Approx. Chi-Square	4040.633
	df	300
	Sig.	.000

Survey Data and Author Calculation

Interpretation: To obtain information about the appropriateness of the data for factor analysis, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity are important. The KMO value is found to be 0.946, which is considered excellent and appropriate size of the sample and the data for performing Factor Analysis. If the KMO value is greater than 0.9, the correlations between the variables are considered good enough that factor extraction can be continued.

The Bartlett's Test of Sphericity is used to test the null hypothesis of no correlation between variables

(variables are unrelated). The Approximate Chi-Square is 4040.633, with 300 degrees of freedom, and a significant P value of 0.000, which means that the null hypothesis may be rejected. This result indicates that the correlation matrix is not an identity matrix, which shows a sufficient level of correlation between the variables for factor analysis to be employed. The KMO value and Bartlett's Test of Sphericity both strongly suggest that the data is suitable for factor analysis, and the results indicate that there are meaningful factor structures that can be derived from the data.

5.4 Confirmatory Factor Analysis

5.4 Model Estimates and Psychometric properties of Constructs

Construct	Items	Factor Loadings	Sum of Factor Loadings	Item Reliability (Squared Factor Loadings)	Delta (Error Variance)	Sum of Delta	AVE (Average Variance Extracted)	CR (Composite Reliability)
AI Adoption	AI1	0.916	3.63	0.839	0.161	1.486	0.7028	0.892
	AI2	0.867		0.751	0.249			
	AI3	0.787		0.619	0.381			
	AI4	0.823		0.676	0.324			
	AI5	0.793		0.629	0.371			
Green Transformation	GT1	0.734	3.874	0.539	0.461	1.993	0.6014	0.82
	GT2	0.776		0.601	0.399			
	GT3	0.828		0.686	0.314			
	GT4	0.792		0.627	0.373			
	GT5	0.744		0.554	0.446			
Innovation	IN1	0.819	3.99	0.671	0.329	1.814	0.6372	0.848
	IN2	0.818		0.669	0.331			
	IN3	0.792		0.628	0.372			
	IN4	0.794		0.63	0.37			
	IN5	0.767		0.588	0.412			
Productivity	PR1	0.804	3.798	0.646	0.354	2.032	0.6736	0.849
	PR2	0.763		0.582	0.418			
	PR3	0.802		0.643	0.357			
	PR4	0.761		0.58	0.42			
	PR5	0.719		0.517	0.483			
Sustainability	SU1	0.711	4.228	0.531	0.469	2.006	0.5988	0.818
	SU2	0.776		0.601	0.399			
	SU3	0.757		0.573	0.427			
	SU4	0.809		0.657	0.343			
	SU5	0.795		0.632	0.368			

Survey Data and Author Calculation

Interpretation: The key statistics from the measurement model analysis for five constructs, namely, AI Adoption, Green Transformation, Innovation, Productivity, and Sustainability, are summarized in the table. Multiple indicators are used to represent each construct, and the degree of relationship between the indicators and the construct is represented by the factor loadings. The item reliability (squared factor loadings) indicates the degree of consistency of each item with its construct. AI1, for example, has an item reliability of 0.839, which indicates that it is a strong indicator of AI Adoption.

The Sum of Delta is the total variance in scores for all the items in each construct. AI Adoption, for example, has a Sum of Delta of 1.486, which indicates the unexplained variance in all indicators for AI Adoption. Like that, the AVE (Average Variance Extracted) of each construct is computed as the mean of the squared factor loadings, with factor loadings > 0.50 indicating that the items in each construct account for > 50% of the variance. The AVE for all constructs (AI Adoption = 0.7028, Green Transformation = 0.6014, Innovation = 0.6372, Productivity = 0.6736, and Sustainability = 0.5988) are higher than this threshold, which suggests good construct validity.

Last, the Composite Reliability (CR) values (ranging from 0.818 for Sustainability to 0.892 for AI Adoption) indicate good internal consistency for the constructs (with values higher than 0.7). All these results indicate that the measurement model has strong construct validity and internal consistency, which allows for further analysis and testing of hypotheses.

5.5 Discriminant Validity of Constructs (Fornell–Larcker Criterion)

Construct	AI Adoption	Green Transformation	Innovation	Productivity	Sustainability
AI Adoption	0.839				
Green Transformation	0.766	0.776			
Innovation	0.901	0.683	0.818		
Productivity	0.806	0.638	0.702	0.804	
Sustainability	0.636	0.66	0.796	0.732	0.795

Survey Data and Author Calculation

Interpretation: To test the discriminant validity of the constructs in the measurement model, the Fornell-Larcker Criterion was used. The diagonal values are the square root of the Average Variance Extracted (AVE) for each construct and the off-diagonal values are the correlations between the constructs. To prove the discriminant validity, the square root of the AVE of each construct must be larger than the other constructs. The square roots of the AVE values are higher for all constructs (AI Adoption 0.839, Green Transformation 0.776, Innovation 0.818, Productivity 0.804, and Sustainability 0.795) than the respective correlations of the constructs with the others. This shows that each construct is clearly separate from the others and so has little overlap, it is said to have discriminant validity. The results have shown that the measurement model is able to capture the separate dimensions and thus the constructs will measure different aspects of the research domain without any significant overlap. This gives assurance about the validity of the constructs used in the study which helps in the robustness of the model.

5.6 Structural Model Evaluation.

5.6.1 Model Fit Indices

The model fit summary shows that the default model fits the data well, with some indices suggesting its adequacy. For the default model, the Chi-Square (CMIN) is 379.011, with 271 degrees of freedom, and a p-value of 0.000, indicating that the model is a good fit for the data. The ratio of CMIN/DF is 1.399 which is below the threshold value of 3 and further indicates that the model fits well. Further, RMR is 0.190 and GFI is 0.884, both are acceptable and AGFI is 0.861 and PGFI is 0.737, showing the acceptable fit of the model, and considering the complexity of the model.

Other fit indices, such as Baseline Comparisons, demonstrate good fits. The model has excellent fits, with the Normed Fit Index (NFI) ranging from 0.910 to 0.973, the Relative Fit Index (RFI) between 0.910 and 0.973, the Tucker Lewis Index (TLI) from 0.939

to 0.980, and the Comparative Fit Index (CFI) from 0.938 to 0.980. The values are near to 1.0 and indicate that the model is a good representation of the data. Parsimony-Adjusted Measures of 0.903, 0.822, and 0.878 for the PRATIO, PNFI, and PCFI, respectively, indicate that the model is a good compromise between fit and complexity.

The default model has a Root Mean Square Error of Approximation (RMSEA) of 0.041 (90% CI: 0.031, 0.050) and a PCLOSE of 0.945, which denotes a very good model fit. The Akaike Information Criterion (AIC) value of 487.011 is less than the AIC value for saturated and independence models, thus supporting the parsimony and fit of the default model. The Expected Cross-Validation Index (ECVI) is 2.038, which is less than the saturated model (2.720) and is much less than the independence model (17.790), further supporting the suitability of this model.

The Hoelter's Critical N (HOELTER) values at the 0.05 (196) and 0.01 (207) significance levels are also greater than most commonly used values which, as indicated, demonstrate that the size of the sample was large enough to support the model. In general, all of the indices show a strong support for the default model, a very good fit in terms of RMSEA, CFI, TLI, AIC, ECVI.

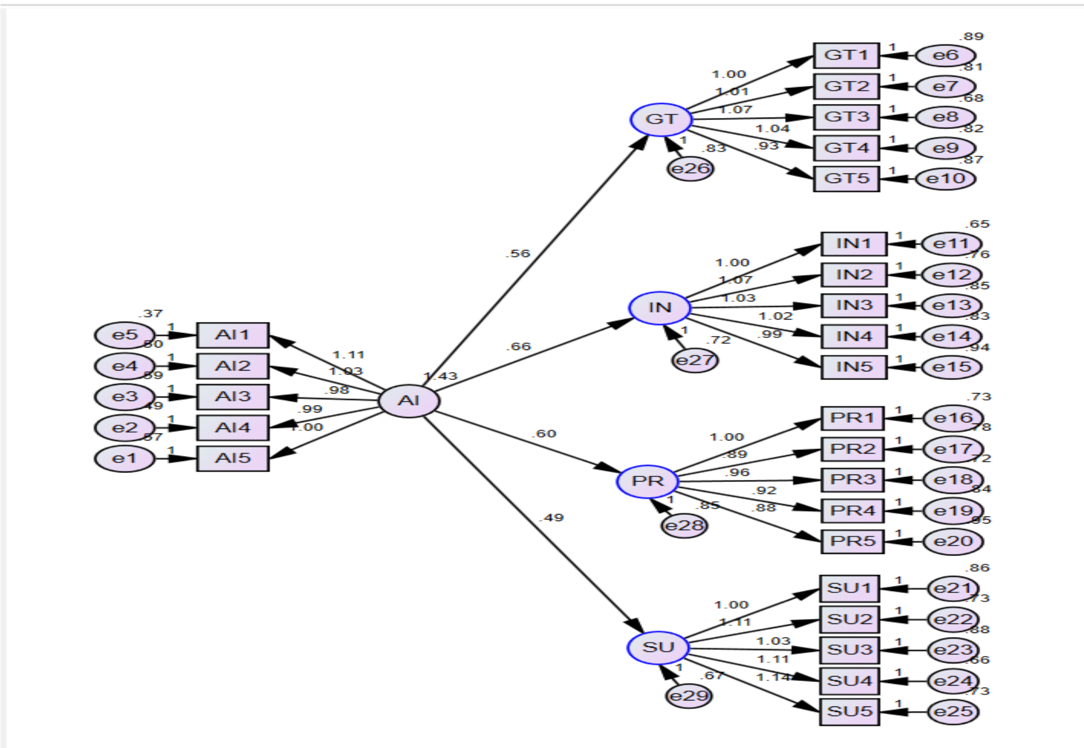

Figure 1: Structural Equation Model

5.6.2 Summary of Structural Equation Model

The relationships between the central construct, Artificial Intelligence (AI), and four dependent constructs: Green Transformation (GT), Innovation (IN), Productivity (PR), and Sustainability (SU) are represented in the Structural Equation Model (SEM) path diagram. The arrows that go from AI to these dependent variables show how AI affects each variable. The path coefficient between AI and Green Transformation is 0.43, which is a moderate positive value, suggesting that there is a moderate level of influence between AI and Green Transformation. The value for the path coefficient between AI and Innovation is 1.11, representing a strong positive relationship, implying that AI has a strong relationship with Innovation. The impact of AI on Productivity (0.60) and Sustainability (0.49) can also be seen, albeit not as pronounced.

The indicators of each construct, including AI1, AI2, and so on, load heavily on their constructs, indicating that the observed variables are good indicators of the constructs. For instance, the factor loading for AI1 is 1.11, which means that this indicator is a strong predictor of the AI construct. Likewise, all the

observed variables load well on their corresponding constructs; the loadings of GT1 are 0.89, IN1 is 1.00, PR1 is 0.96 and SU1 is 1.11. The high loadings indicate that the indicators are measuring the constructs well.
This is an important feature of the SEM model where the residuals (e1, e2, etc.) are the unexplained variance for each observed variable. For example, there is a residual of 0.37 for indicator AI1, indicating that 37% of the variance in this indicator is unexplained by the AI construct. The overall model shows that AI has a strong influence on the improvement of Green Transformation, Innovation, Productivity and Sustainability, to different degrees. These connections between AI and these elements highlight the critical importance of AI in driving organizational performance, especially in the context of innovation and sustainability.

5.6.3 Hypothesis Testing

Hypothesis	Estimate	Standardized Estimate	S.E.	C.R.	p-value	Result
H1: AI Adoption → Green Transformation	0.562	0.595	0.067	8.379	***	Supported
H2: AI Adoption → Innovation	0.659	0.68	0.066	10.064	***	Supported
H3: AI Adoption → Productivity	0.596	0.612	0.068	8.82	***	Supported
H4: AI Adoption → Sustainability	0.49	0.581	0.061	7.982	***	Supported

Survey Data and Author Calculation

Interpretation: The outcome of hypothesis testing supports the fact that the adoption of Artificial Intelligence (AI) has a significant impact on all four dependent constructs, namely: Green Transformation (GT), Innovation (IN), Productivity (PR) and Sustainability (SU). The results of the four hypotheses are strongly confirmed by the significant path coefficients and positive standardized estimates. Specifically, AI Adoption has a moderate to strong positive impact on Green Transformation (estimate = 0.562, standardized estimate = 0.595), Innovation (estimate = 0.659, standardized estimate = 0.680), Productivity (estimate = 0.596, standardized estimate = 0.612), and Sustainability (estimate = 0.490, standardized estimate = 0.581). All critical ratios (C.R.) and p-values are greater than 7.0 and lower than 0.001 (α=0.01), respectively, indicating that all the relationships are statistically significant at 99% confidence level. These results emphasize the pivotal role that AI adoption plays in driving advancements in Green Transformation, Innovation, Productivity, and Sustainability, providing strong support for the proposed model.

VI. DISCUSSION

This study's results underscore the crucial role of AI Adoption in Green Transformation, Innovation, Productivity, and Sustainability. These constructs were demonstrated to be positively related to AI adoption, thereby highlighting its potential role in promoting sustainable practices, innovation, and organizational efficiency. These findings corroborate those of previous research in certain areas, such as green transformation, where AI optimises resources and decision making (Huang et al., 2020). The impact of AI on innovation and productivity has already been seen, with research highlighting its ability to streamline processes and enhance operational effectiveness (Brynjolfsson & McAfee, 2017). Moreover, AI's role in sustainability aligns with research indicating that AI aids in achieving sustainability objectives, including energy usage reduction and pollution reduction. In conclusion, this research underscores the transformative power of AI in the pursuit of sustainable practices, productivity gains, and innovation in various sectors.

VII. CONCLUSION AND FUTURE RESEARCH

Finally, this study proves that AI plays a significant role in Green Transformation, Innovation, Productivity and Sustainability, while its transformative power is evident in the journey of the organizations. The positive associations of AI with these key constructs highlight the potential of AI technologies to boost industries' sustainability, innovation and productivity. The results provide valuable insights into how AI tools can impact organizational performance and their potential for businesses to achieve competitive advantage and sustainability objectives.

Researchers might investigate the exact ways in which AI affects these constructs, specifically across different sectors or regions. A longitudinal study would yield greater insight into the impact of AI over time, on organizational performance. In addition, examining the issues and obstacles to AI implementation in small enterprises may provide valuable insights into how to encourage wider implementation of AI in industries dealing with sustainability and innovation.

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