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The Influence of Artificial Intelligence on Sustainable Development in the IT Sector in Coimbatore

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ABSTRACT

In the modern industrial era, the intersection of technological innovation and environmental responsibility has become a focal point for global progress. The problem addressed in this study is the lack of impact on how Artificial Intelligence influences sustainable development within the IT sector of Coimbatore. To address this problem the author developed two research questions: They are i) To what extent do demographic profiles significantly influence AI-related attitudes among IT sector professionals? ii) What is the impact of Artificial Intelligence integration on sustainable development practices within the IT sector?. The result shows environmental sustainability is primarily driven by perceived risk management, while social and governance impacts are driven by perceived usefulness. Concluded as organizations should prioritize risk-mitigation features for environmental goals and high-utility, value-driven applications for social and governance initiatives.

Keywords: *Impact, Regression, Environment (E), Social (S), Governance (G), Perceived Trust, Risk, Usefulness and Easy to Use.*

JEL Classification: *C25, C83, H19, 03, Q01*

Introduction

Artificial Intelligence (AI) has emerged as one of the most transformative technologies of the 21st century, reshaping industries, economies, and societies across the globe. From intelligent automation and predictive analytics to machine learning–driven decision-making systems, AI is redefining how organizations operate and deliver value. In the context of sustainable development, AI offers significant potential to enhance efficiency, optimize resource utilization, reduce environmental impact, and promote inclusive economic growth. As nations align their policies with the goals of the United Nations Sustainable Development Goals (SDGs), the integration of AI into various sectors has become a strategic priority.

The Information Technology (IT) sector, being both a driver and beneficiary of digital transformation, plays a pivotal role in advancing sustainable development. By leveraging AI technologies such as machine learning, natural language processing, and data analytics, IT companies can improve energy efficiency in data centers, streamline software development processes, enhance cyber-security, and support environmentally responsible business practices. At the same time, AI-enabled solutions contribute to broader sustainability objectives, including smart resource management, reduced carbon footprints, and socially responsible innovation.

In India, cities like Coimbatore have emerged as important IT and industrial hubs, fostering technological advancement alongside economic growth. Known for its strong entrepreneurial culture, skilled workforce, and expanding IT infrastructure, Coimbatore is increasingly adopting AI-driven solutions across start-ups, software firms, and technology parks. The city's evolving digital ecosystem presents a unique opportunity to examine how AI influences sustainable practices within a rapidly growing regional IT sector.

This study explores the influence of Artificial Intelligence on sustainable development within the IT sector of Coimbatore. It seeks to analyze how AI technologies contribute to environmental sustainability, economic efficiency, and social development in the region. By understanding the intersection between AI innovation and sustainability objectives, the research aims to highlight both opportunities and challenges, offering insights into how emerging technologies can support long-term, responsible growth in a dynamic urban IT landscape.

Review of Literature

Popa (Switzerland) / Raluca-Giorgiana (Chivu) (2025) focused on the drivers of consumers' adoption of artificial intelligence (AI)-enabled technology solutions. A quantitative and cross-sectional design was applied in exploring the determinants of consumer adoption of AI-enabled tools. A structured online survey was conducted using the existing literature scales modified to align with the topic of investigation and the use of AI in personal and professional settings. The participants included individual consumers with various levels of experience with AI-enabled applications. Non-probability purposive sampling was adopted to ensure participation from individual users with at least some knowledge about AI-enabled applications (such as smart assistants, recommendation engines, and AI chatbots). In total, 240 valid responses were obtained within one month. The results indicate that cognitive (e.g., usefulness and ease of use), affective (e.g., attitudes and intrinsic motivation), and contextual (e.g., work experience) factors are essential in determining the behavioral intention for adopting AI solutions. Particularly, trust in AI systems was identified as an important mediating factor, while marketing personalization had the greatest impact on trust, suggesting the importance of user-centric interaction designs.

Anamaria Nastasa (2024) The current study is dedicated to examining the core themes associated with artificial intelligence (AI) and sustainable development in the era of the pandemic. This review represents an exploration of the scientific literature concerning artificial intelligence and sustainability from the outset of the pandemic to 2023. The current paper examines the scientific literature focusing on both the positive and negative aspects of the effects of artificial intelligence on the SDGs. For this research, we applied bibliometric analysis and text mining methods to determine the core themes discussed in the literature published in the Web of Science and Scopus databases. Firstly, they relied on descriptive statistics to determine the influence of authors, publications per countries, key terms, and other descriptive statistics. The authors' study uncovered different themes within the existing literature that touch upon the topic of AI and sustainable development. The themes comprise social sustainability, health issues, energy-efficient AI technologies, sustainable industries and innovations, Internet of Things (IoT) technologies to create smart and sustainable cities, urban planning, technologies for education and knowledge creation, and technology influence on SDGs. Moreover, the authors have revealed that there is an obvious positivity bias in the literature about the impact of AI on sustainable development.

Xiao Yuping, Xiao Li - china, philippines (2025) In recent years, the development of artificial intelligence technology and its applications in corporate management has accelerated. Using artificial intelligence technology to improve ESG and support sustainable development has become one of the major issues studied by scholars and professionals in practice. This study seeks to investigate the effect of artificial intelligence in ESG on the sustainable development of central state-owned enterprises in China. Specifically, the research will examine the role of artificial intelligence technology in corporate governance, environmental protection, and social responsibility. Its contribution to the sustainability of enterprises will be analyzed in detail. The research uses the survey method to collect data from 200 managers and employees of Central State-owned enterprises. There are 15 questions in the survey instrument, which consists of three dimensions, namely corporate governance, environmental protection, and social responsibility. The findings reveal that the respondents' perception towards central state-owned enterprises regarding corporate governance, environmental protection, and social responsibility is very positive, especially when it comes to social responsibility. Moreover, a model for regression analysis has been developed. The findings reveal that artificial intelligence technology may help to improve central state-owned enterprises and their sustainable development.

Statement of the Problem

The rapid advancement of Artificial Intelligence (AI) has significantly transformed the global Information Technology (IT) sector, creating new opportunities for innovation, efficiency, and economic growth. As organizations increasingly align their strategies with the Sustainable Development Goals (SDGs) proposed by the United Nations, the integration of AI technologies is viewed as a critical driver for achieving sustainable development. AI has the potential to optimize resource utilization, reduce energy consumption, enhance productivity, and support environmentally responsible business practices. However, the actual impact of AI on sustainability outcomes varies depending on regional ecosystems, technological readiness, and organizational capabilities. In India, the IT industry plays a vital role in national economic development, and emerging technology hubs are increasingly adopting AI-driven solutions. Coimbatore has evolved into a growing IT and industrial center, characterized by expanding software firms, start-ups, and technology parks. While AI adoption in Coimbatore IT sector is steadily increasing, there is limited empirical evidence assessing how these technologies influence sustainable development in terms of environmental performance, social responsibility and governance efficiency within the region. Despite the recognized potential of AI to promote sustainability, concerns remain regarding high energy consumption of AI systems, data privacy issues, skill gaps, and unequal access to technological resources. Furthermore, small and medium-sized IT enterprises in Coimbatore may face challenges in integrating AI sustainably due to financial constraints and lack of specialized expertise. The absence of localized research examining these dynamics creates a gap in understanding whether AI implementation genuinely contributes to sustainable development.

Therefore, the problem addressed in this study is the lack of impact on how Artificial Intelligence influences sustainable development within the IT sector of Coimbatore. This research seeks to investigate the extent to which AI adoption supports environmental sustainability, social well-being and governance efficiency.

Research Questions

- To what extent do demographic profiles significantly influence AI-related attitudes among IT sector professionals?
- What is the impact of Artificial Intelligence integration on sustainable development practices within the IT sector?

Objectives of the Study

- To investigate whether demographic profiles and AI-related attitudes differ significantly among IT sector professionals.
- To examine the impact between AI and Sustainability Development in the IT sector.

Hypotheses of the Study

H_{01}: There is no significant association between demographic profile and AI related factors among IT sector employees.

H_{02}: There is no impact between AI adoption and Sustainability Development.

Research Methodology

The current research will adopt a quantitative research design and will also use an analytical approach, where primary data will be collected from IT professionals based in Coimbatore. Although there are around 750 IT companies functioning in this region, this research will particularly concentrate on five major companies: CTS, Bosch, Wipro, Infosys, and TCS, based on their huge employee count for the 2025-2026 period. With a simple random sampling approach, a sample size of 43 employees has been determined for this research to avoid biased data collection. The data collection for this research will take place in December 2025 and January 2026, and Chi-square and regression analysis will be performed to check the relationships. Constructs: perceived usefulness, perceived easy to use, perceived trust, perceived risk, and for sustainability development, the constructs used for this research are environment, social, and governance. The tools used for this research are chi-square, reliability, and correlation.

Analysis and Results

Table 1: Demographic Profile and Chi-Square Analysis

		CTS	Bosch	Wipro	Infosys	TCS	Total	Chi-Square (P Value)
Gender	female	0	1	2	0	3	**6**	**.003****
	male	15	5	9	7	1	**37**	
	Total	**15**	**6**	**11**	**7**	**4**	**43**	
age	<=25	9	5	10	1	3	**28**	**.048***
	25-35	3	1	1	5	1	**11**	
	36-45	3	0	0	1	0	**4**	
	>45	0	0	0	0	0	**0**	
	Total	**6**	**15**	**7**	**4**	**11**	**43**	

Marital Status	Married	3	0	2	3	0	**8**	**.285**
	Unmarried	12	6	9	4	4	**35**	
	Total	**15**	**6**	**11**	**7**	**4**	**43**	
Education Qualification	UG	12	5	11	4	4	36	**.153**
	PG	3	1	0	3	0	7	
	Total	**6**	**15**	**7**	**4**	**11**	**43**	
Type of Education	Arts & Science	8	5	7	4	0	24	**.125**
	Engineering	7	1	4	3	4	19	
	Total	**15**	**6**	**11**	**7**	**4**	**43**	
Years of Experience in IT sector	<=5	11	6	10	3	4	**34**	**.547**
	6-10	1	0	1	1	0	**3**	
	11-15	1	0	0	1	0	**2**	
	>15	2	0	0	2	0	**4**	
	Total	**15**	**6**	**11**	**7**	**4**	**43**	
Income per Month	<=Rs.50,000	10	5	9	3	4	31	**.284**
	Rs.50,001-1,00,000	2	1	9	3	4	7	
.ygyg	Rs.1,00,001-1,50,000	0	0	0	1	0	1	
.284	> Rs.1,50,000	3	0	1	0	0	4	
	Total	**15**	**6**	**11**	**7**	**4**	**43**	
Awareness of AI	yes	15	6	10	7	4	42	**.561**
	No	0	0	1	0	0	1	
	Total	**15**	**6**	**11**	**7**	**4**	**43**	
Usage Method of AI tool	Personally (Free)	12	5	8	1	2	28	**.051***
	Personally (paid)	0	0	1	1	0	2	
	Subscribed with company itself	2	1	3	3	0	9	
	Personally (free) + subscribed by company itself	1	0	0	1	2	4	
	Used All	**0**	**0**	**0**	**1**	**0**	**1**	
	Total	**15**	**6**	**11**	**7**	**4**	**43**	

Source: primary data

The Table 1 indicates demographic and AI-related factors differ significantly among employees of selected IT sector. The results reveal a statistically significant association between gender and organization (p = 0.003). This indicates that the distribution of male and female employees differs significantly across the selected companies, suggesting variation in gender composition among the organization. Similarly, age shows a significant association with organization (p = 0.048). This finding implies that employees of different age groups are not uniformly distributed across the companies, with certain organizations having a higher concentration of respondents in specific age categories.

In contrast, marital status does not exhibit a significant association with organization (p = 0.285). This indicates that married and unmarried respondents are proportionately distributed across all companies. Likewise, educational qualification (p = 0.153) and type of education (p = 0.125) do not show significant relationships with organization, suggesting that employees' academic background is similar across the selected firms.

Further, the analysis indicates that years of experience in the IT sector is not significantly associated with organization (p = 0.547). This suggests a relatively uniform distribution of employees with varying levels of experience among the companies. Monthly income also does not demonstrate a significant association with organization (p = 0.284), indicating comparable income structures across the organizations.

With regard to AI-related factors, awareness of AI tools does not show a significant association with organization (p = 0.561), reflecting a high and consistent level of awareness among respondents across all companies. Additionally, the method of usage of AI tools does not exhibit a statistically significant relationship with organization (p = 0.051). Although this value is marginally above the threshold level, it does not provide sufficient evidence to conclude a significant association.

Table 2: Regression Analysis Model Summary of Environment Sustainability and AI Adoption

Model Summary				
Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**
1	.701[a]	.491	.438	1.91408
a. Predictors: (Constant), Perceived_Risk, Perceived_Usefulness, Perceived_Trust, Perceived_Easy_Of_Use				

Source: Primary Data

The above table 2 displays the model summary for the impact of environment sustainability and AI adoption. When the environment sustainability is Dependent Variable, R is .701 which means that there is strong positive correlation. R-Square is .491 which indicated 49.1% of impact is accounted. Adjusted R Square Value is .438, implying that slightly lower than R Square (.438 vs .491), it suggests that while your predictors are meaningful, the model's complexity is being accounted for to prevent overfitting the model has accounted for 43.8% of variance in the environment sustainability. Std. Error of the Estimate represents the average distance that the observed values fall from the regression line typically off by about 1.91 units in the scale of dependent variable.

Table 3: Regression Analysis Anova of Environment Sustainability and AI Adoption

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	134.453	4	33.613	9.175	.000[b]
	Residual	139.221	38	3.664		
	Total	273.674	42			
a. Dependent Variable: Environmental_Sustainability						
b. Predictors: (Constant), Perceived_Risk, Perceived_Usefulness, Perceived_Trust, Perceived_Easy_Of_Use						

Source: Primary Data

The table 3 Clarifies the Anova for environment sustainability and AI adoption. ANOVA table shows the significant value of .000 Which is less than 0.05 level of significant. So, it can be concluded that environment sustainability and AI adoption is Highly Significant. Hence, the null hypothesis is rejected at 1% level of significant.

Table 4: Regression Analysis Coefficients of Environment Sustainability and AI Adoption

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.749	1.064		1.644	.108
	Perceived_Usefulness	.190	.189	.257	1.006	.321
	Perceived_Easy_Of_Use	.213	.205	.293	1.042	.304
	Perceived_Trust	-.071	.127	-.122	-.560	.579
	Perceived_Risk	.245	.106	.361	2.310	.026
a. Dependent Variable: Environmental_Sustainability						

Source: Primary Data

The above table 4 displays the coefficient for impact of environment sustainability and AI adoption. It implies that except perceived risk (.026) other variables are such as perceived usefulness, perceived easy to use and perceived risk has the p value above 0.05. Hence the null hypothesis is rejected for perceived risk.

Table 5: Regression Analysis Model Summary of Social Sustainability and AI Adoption

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.745[a]	.556	.509	5.18822
a. Predictors: (Constant), Perceived_Risk, Perceived_Usefulness, Perceived_Trust, Perceived_Easy_Of_Use				

Source: Primary Data

The above table 5 displays the model summary for the impact of Social sustainability and AI adoption. When the Social Sustainability is Dependent Variable, R is .745 which means that there is strong positive correlation. R-Square is .556 which indicated 55.6% of impact is accounted. Adjusted R Square Value is .509, implying that slightly lower than R Square (..556 vs .509), it suggests that while your predictors are meaningful, the model's complexity is being accounted for to prevent overfitting the model has accounted for 50.9% of variance in the Social Sustainability. Std. Error of the Estimate represents the average distance that the observed values fall from the regression line typically off by about 5.19 units in the scale of dependent variable which indicates moderately high for the sample 43.

Table 6: Regression Analysis Anova of Social Sustainability and AI Adoption

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1278.804	4	319.701	11.877	.000[b]
	Residual	1022.871	38	26.918		
	Total	2301.674	42			
a. Dependent Variable: Social_Sustainability						
b. Predictors: (Constant), Perceived_Risk, Perceived_Usefulness, Perceived_Trust, Perceived_Easy_Of_Use						

Source: Primary Data

The table 6 Clarifies the Anova for Social Sustainability and AI adoption. ANOVA table shows the significant value of .000 Which is less than 0.05 level of significant. So, it can be concluded that environment sustainability and AI adoption is Highly Significant. Hence, the null hypothesis is rejected at 1% level of significant.

Table 7: Regression Analysis Coefficients of Social Sustainability and AI Adoption

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.912	2.885		1.356	.183
	Perceived_Usefulness	1.389	.512	.646	2.711	.010
	Perceived_Easy_Of_Use	.412	.554	.195	.742	.462
	Perceived_Trust	-.109	.343	-.065	-.319	.752
	Perceived_Risk	-.090	.288	-.046	-.313	.756
a. Dependent Variable: Social_Sustainability						

Source: Primary Data

The above table 7 displays the coefficient for impact of Social Sustainability and AI adoption. It implies that except perceived usefulness (.010) other variables are such as perceived trust, perceived easy to use and perceived risk has the p value above 0.05. Hence the null hypothesis is rejected for perceived usefulness.

Table 8: Regression Analysis Model Summary of Governance Sustainability and AI Adoption

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.694[a]	.482	.428	2.58366
a. Predictors: (Constant), Perceived_Risk, Perceived_Usefulness, Perceived_Trust, Perceived_Easy_Of_Use				

Source: Primary Data

The above table 8 displays the model summary for the impact of Governance Sustainability and AI adoption. When the Governance Sustainability is Dependent Variable, R is .694 which means that there is moderate to strong positive correlation. R-Square is .482 which indicated 48.2% of the changes is accounted. Adjusted R Square Value is .428, implying that slightly lower than R Square (..482 vs .428), it suggests that model is a good fit because the value isn't drastically lower than the regular R square. Std. Error of the Estimate represents the average distance that the observed values fall from the regression line typically off by about 2.58 units in the scale of dependent variable which indicates accurate for the sample 43.

Table 9: Regression Analysis Anova of Governance Sustainability and AI Adoption

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	236.106	4	59.026	8.843	.000[b]
	Residual	253.662	38	6.675		
	Total	489.767	42			
a. Dependent Variable: Governance_Sustainability						
b. Predictors: (Constant), Perceived_Risk, Perceived_Usefulness, Perceived_Trust, Perceived_Easy_Of_Use						

Source: Primary Data

The table 9 Clarifies the Anova for Governance Sustainability and AI adoption. ANOVA table shows the significant value of .000 Which is less than 0.05 level of significant. So, it can be concluded that Governance Sustainability and AI adoption is Highly Significant. Hence, the null hypothesis is rejected at 1 percent level of significant.

Table 10: Regression Analysis Coefficients of Governance Sustainability and AI Adoption

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.554	1.437		1.778	.083
	Perceived_Usefulness	.550	.255	.555	2.156	.037
	Perceived_Easy_Of_Use	.173	.276	.177	.625	.536
	Perceived_Trust	-.078	.171	-.101	-.457	.650
	Perceived_Risk	.098	.143	.108	.687	.497
a. Dependent Variable: Governance_Sustainability						

Source: Primary Data

The above table 10 displays the coefficient for impact of Governance Sustainability and AI adoption. It implies that except perceived usefulness (.037) other variables such as perceived trust, perceived easy to use and perceived risk has the p value above 0.05. Hence the null hypothesis is rejected for perceived usefulness at 5 percent level of significant.

Findings

Model Summary of Environment, Social and Governance sustainability and AI adoption

- The models are highly effective at explaining the variance in sustainability. Social Sustainability is the most strongly influenced by AI adoption, with the model explaining 50.9% (Adjusted) of its variance. This is followed by Environmental Sustainability (43.8%) and Governance Sustainability (42.8%). In statistical terms, explaining nearly half of the variance in such complex fields indicates that AI adoption is a primary driver of ESG outcomes.
- All three dimensions show a strong positive correlation (R-values between .694 and .745). This confirms that as AI adoption increases, there is a consistent and predictable improvement in Environmental, Social, and Governance metrics. The strongest relationship exists between AI and Social Sustainability (R = .745).
- Across all three models, the Adjusted R-Square values remain close to the R-Square values. This is a critical finding because it proves that your predictors (Perceived Usefulness, Risk, etc.) are truly meaningful and the results are not just a result of a complex model "forcing" a fit.
- The Standard Error of the Estimate shows that the Environmental model is the most "precise" (off by only 1.91 units), while the Social Sustainability model shows higher volatility (off by 5.19 units). This suggests that while AI has a huge impact on Social Sustainability, that impact is more varied across the sample compared to the more consistent results seen in Environmental sustainability.

ANOVA of Environment, Social and Governance sustainability and AI adoption

- Across all three pillars—Environmental, Social, and Governance—the p-value is .000. Since this is well below the standard threshold of 0.05 (and even the stricter 0.01), we can conclude with 99% confidence that the relationship between AI adoption and ESG sustainability is not due to random chance.
- The ANOVA results confirm that your independent variables (like Perceived Usefulness, Risk, etc.) collectively do a great job of predicting the "outcome" (ESG sustainability). It proves that the "Impact" you found in your Model Summary (the R-Square values) is statistically real and reliable.

Coefficients of Environment, Social and Governance sustainability and AI adoption

- Only Perceived Risk (p=.026) is a significant predictor of environmental sustainability. Variables like "Ease of Use" and "Usefulness" do not significantly influence the environmental outcome. This suggests that stakeholders view AI's role in the environment primarily as a risk-management tool. The impact on the environment is tied to how AI handles threats, hazards, or ecological risks rather than how "handy" or "easy" the tool is.
- Only Perceived Usefulness (p=.010) is a significant predictor. For social impact, "Trust," "Risk," and "Ease of Use" fall away as non-significant. This indicates a pragmatic perspective: AI impacts social sustainability simply because it is useful. If the AI effectively solves social problems or improves human welfare, it creates an impact, regardless of whether people find it "easy" to operate or "trustworthy" in a general sense.

- Only Perceived Usefulness (p=.037) is a significant predictor. Similar to the Social pillar, Governance is moved by the utility of the AI. Factors like "Trust" and "Ease of Use" did not reach the 0.05 significance level. This suggests that for corporate governance and transparency, the primary driver is the functional value AI brings to the table (e.g., better data auditing or reporting).

Suggestions

- For Environmental sustainability, Perceived Risk is the only significant predictor. This suggests that stakeholders view AI as a tool for environmental protection primarily through the lens of risk management (e.g., using AI to prevent environmental disasters or monitor compliance).
- For both Social and Governance pillars, Perceived Usefulness is the winner. This means people believe AI contributes to social welfare and corporate transparency because it is effective at those tasks, regardless of whether it is easy to use or "trusted."
- Across all three models, "Perceived Ease of Use" was not significant. This implies that for ESG goals, the complexity of the AI doesn't matter; what matters is whether it gets the job done (Usefulness) or keeps things safe (Risk).

Conclusion

AI adoption is a powerful predictor of ESG performance, accounting for approximately half of the changes observed in sustainability outcomes. The study concludes that AI adoption acts as a major driver for ESG sustainability, explaining up to 50.9% of performance variance and showing the strongest impact on the social dimension. Data suggests a utilitarian trend where stakeholders prioritize AI's functional, risk-mitigating outcomes over user-friendly interfaces, with environmental efforts driven by risk management and social/governance efforts driven by utility. Strategic recommendations include shifting development toward functional robustness, framing environmental AI as a compliance tool, and leveraging tangible utility for social and governance initiatives.

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