Generative Artificial Intelligence and Green Choices: Exploring Environmental Attitudes and Digital Behaviour in India

Jyothi CHITTINENI
IBS- Hyderabad, ICFAI Foundation for Higher Education (IFHE), Hyderabad, India
https://orcid.org/0000-0002-3838-6995

Palanikumar MAHESWARI
SRM Institute of Science and Technology, Ramapuram, India
https://orcid.org/0000-0002-9167-0047

Chellamuthu SAHILA
SRM Institute of Science and Technology, Ramapuram, India
https://orcid.org/0000-0003-1691-7035

Sathyamurthy BALAKRISHNAN
SRM Institute of Science and Technology, Ramapuram, India
https://orcid.org/0000-0002-2848-7792

Abstract:

The proliferation of Generative AI (GenAI) tools has introduced new dynamics in user behaviour, environmental perception, and digital sustainability. This study, based on a primary questionnaire survey of 1,005 GenAI users aged 18 and above from India, investigates the frequency of GenAI usage and its relationship with climate change awareness, environmental concern, and willingness to adopt energy-efficient digital practices. Using regression-based models, the research reveals a pattern of indirect dependence: lower GenAI usage is related with a greater inclination toward environmentally responsible behaviours, such as transitioning from non-sustainable platforms and adopting energy-efficient digital services. In contrast, frequent GenAI users tend to perceive climate change as temporally distant and of lower immediate importance.

The study also examines how the frequency and nature of social media usage influence users' attitudes toward sustainable technology choices. These findings provide valuable insights for policymakers, AI educators, digital strategists, and sustainability advocates aiming to foster environmentally conscious technology adoption in emerging economies like India.

Keywords: generative AI, environmental attitudes, climate change awareness, digital sustainability, energy-efficient practices.

Introduction

As GenAI technologies evolve, their environmental impact has gained much attention. The remarkable capabilities of these models, such as language generation, content and Image creation, are coupled with significant energy consumption and associated carbon emissions. Understanding these concerns is crucial in shaping future AI development and deployment practices. Building and running AI models, particularly those with numerous parameters, such as chatGPT, require substantial computational resources. These resources translate into high electricity usage, often sourced from non-renewable energy.

Training GPT-3 module can consume up to 1287 MWh of electricity, generating a carbon footprint that equals that of several gasoline-powered vehicles over a year. This suggests that while advancements in AI can lead to breakthroughs in various fields, they also pose significant challenges to sustainability. The green AI concept has emerged as a response to these challenges and a means of advocating sustainable practices within the AI community. Green AI emphasizes the importance of efficiency in AI research and development, encouraging researchers to prioritize energy-efficient models and methods. This includes optimizing algorithms, utilizing renewable energy sources, and adopting practices that reduce the overall carbon footprint of AI technologies. Several strategies have been proposed to further the goals of Green AI. For instance, focusing on sparsity in AI models can reduce the number of parameters, resulting in lower energy consumption without significantly sacrificing performance.

Supporting green AI initiatives is important for achieving a more sustainable future and advancing technology responsibly. Some researchers have suggested using energy consumption as a key performance measure in deep learning to promote green AI (Bae & Ha, 2021). Rohde et al. proposed a framework that includes 19 sustainability criteria to assess the sustainability of AI systems. At the same time, recent studies show that green AI efforts are making significant progress and offering new opportunities for companies working on AI development (Amankwah-Amoah et al., 2024; Feuerriegel et al., 2024; Sedkaoui & Benaichouba, 2024).

The increasing emphasis on sustainability is fostering a deeper link between AI development, environmental accountability, and social responsibility, areas that have not been addressed in traditional AI frameworks. Generative AI (GenAI) users play a pivotal role, as their actions and choices directly influence the environmental footprint of AI technologies. While other industries have embraced environmental awareness through established policies and support tools, adopting green practices in information and innovative technologies is more complex. It depends mainly on cognitive and psychosocial factors, including users' attitudes and prior experiences with AI in their professional and personal lives.

These dynamics indicate a significant research gap, especially regarding the behavioural patterns and attitudes associated with using GenAI in sustainability. This research examines the environmental attitudes, digital behaviours, and sustainability perceptions of Indian users of GenAI. The research contributes a novel conceptual framework integrating behavioural dimensions with green AI initiatives. This approach also supports the formulation of targeted policies and strategies to foster environmentally conscious use of GenAI technologies.

1. Literature Review

Technological advancements are significantly influencing the discourse surrounding environmental policy. These shifts are reflected in the emergence of differing public attitudes towards technology and its ecological implications (Leipold et al., 2019; Alkaf et al., 2023). In particular, the rise of activist groups that are critical of artificial intelligence (AI) and mainstream climate agendas has sparked resistance and a growing trend of anti-reflective thinking about environmental issues. Some radical viewpoints even frame climate change as a hoax (Lewandowsky, 2021). Scholars have warned about the dangers of organized climate denialism, which enables targeted dissemination of misinformation, thereby muddying public understanding, intensifying political polarization, and undermining climate action (Coan et al., 2021; Almiron et al., 2023).

Recently, the potential of generative AI (GenAI) in addressing pressing societal concerns such as climate change, racial justice, and health disparities has drawn increasing scholarly attention (Chatterjee, 2024). However, limited research has investigated its role across diverse user demographics. For example, Chen et al. (2024) conducted an in-depth algorithmic audit involving ChatGPT-3, analysing user engagement based on educational background, communication style, and perspectives on climate and social justice. Their findings revealed that participants with higher educational levels were more likely to shift their attitudes after interacting with AI, while those with lower educational attainment were less engaged. These insights highlight the importance of designing inclusive AI systems that consider users' socio-economic and educational backgrounds, as such systems can serve as powerful educational tools and influence public attitudes positively (Galaz et al., 2021).

Users' preferences for AI features also differ. Research by Ioku et al. (2024) showed that users prioritize transparency over performance and value performance more than environmental sustainability. Interestingly, individuals with a future-oriented mindset tended to prioritize sustainability more. In contrast, Sarathchandra & Haltinner (2021) found that climate skepticism was often connected with older, male, politically conservative individuals who were more religious, better educated, and wealthier.

Another emerging concern is GenAI's environmental impact, particularly in electronic waste (e-waste). Wang et al. (2024) emphasized the potential of integrating circular economy practices within the green AI lifecycle to reduce e-waste generation by 16% to 86%. Alzoubi and Mishra (2024) categorized green AI efforts into six areas: cloud-based optimization, model efficiency tools, carbon footprint assessment, sustainability-focused tools, open-source initiatives, and green AI communities. Governments are beginning to acknowledge the significance of these initiatives, although formal regulatory frameworks are still evolving (Kirkpatrick et al., 2024). Institutions like the United Nations and the OECD are actively working towards standardizing AI governance practices on the global stage.

Moreover, several scholars argue that GenAI's broader social and environmental consequences, such as high energy usage, unequal accessibility, and labour conditions, are often overlooked during its development and deployment (Hosseini et al., 2024). A significant challenge remains in determining who is responsible for measuring and mitigating these impacts and what tools or frameworks should be employed.

In the context of the digital transformation of the global economy, the exponential rise in data generation, powered by cloud computing, big data analytics, and digital services, has dramatically increased the burden on data center s (Edwards et al., 2024). Globally, there are over 6,000 data centres, and their numbers are projected to grow annually by 15%, with one-third situated in the United States (Brocklehurst, 2021; Hogan, 2023). These facilities play a critical role in digital infrastructure but also contribute significantly to energy consumption. It is estimated that the ICT sector is responsible for 2.1% to 3.9% of global carbon emissions, and data centres alone account for around 45% of this footprint (Dobbe & Whittaker, 2019; Freitag et al., 2021).

Advanced AI systems are especially energy-intensive, particularly those involving deep learning and generative models. They rely on specialized processors such as GPUs and TPUs, which consume much more power than conventional computing devices (Ermakov, 2024). The escalating energy needs of AI-powered data centers pose a threat to other sectors dependent on electricity. The emissions a data center produces can vary dramatically, up to 40-fold, depending on the energy mix of its local grid (Dhar et al., 2022). Therefore, nations must invest in modernizing their energy infrastructure, emphasizing renewable energy integration to ensure both sustainability and affordability.

Green AI initiatives are instrumental in minimizing AI's ecological impact. This includes the development of energy-efficient algorithms, sustainable hardware, and low-emission infrastructure (Alzoubi & Mishra, 2024; Malkova, 2025). Regulatory support through stringent environmental policies can further incentivize the growth of green AI (Polyakov et al., 2021; Radavičius & Tvaronavičienė, 2022). Studies have explored effective ways to reduce the carbon footprint of AI systems (Wang et al., 2023; Chauhan et al., 2024) and evaluated the success of various green technology projects (Levický et al., 2022; Piccinetti et al., 2023). Such projects help mitigate environmental damage and enhance the public image of socially responsible organizations, attracting investors and stakeholders who value sustainability.

2. Research Questions

The reviewed literature highlights a notable fragmentation across existing research studies, stemming from differences in research contexts, frameworks, objectives, and methodologies. This diversity limits the comparability of findings due to variations in data sources, analytical approaches, and the nature of causal relationships explored. However, a unifying thread among these studies is the growing call for systematically exploring public perceptions regarding environmental issues within technological advancement. Moreover, they underscore the evolving role of users as active agents who can shape the sustainable development and application of AI technologies.

In line with these insights, this study aims to investigate the intersection of generative AI (GenAI), environmental awareness, and behavioural change among Indian youth. Notably, no prior research has been conducted in the Indian context on this specific theme, making this study a unique and original contribution to the literature.

R1: How does the engagement of the Indian Population with generative AI influence their awareness and understanding of climate change?

R2: What is the level of willingness among the Indian Population to adapt their behaviours based on the environmental consequences of data centers and generative AI technologies in the digital ecosystem?

3. Data and Methodology

This study adopts the methodological framework and utilizes the Questionnaire previously developed by Moravec, Gavurová, & Kováč, (2025). Annexure 1 contains the detailed Questionnaire. The questionnaire administration and data collection are through an online survey method in India between December 2024 and May 2025. One thousand nine hundred individuals initially participated in the survey, of which 1,005 provided fully completed responses. All valid respondents were above the age of 18. The sample size and data collection use a random selection process to ensure representativeness across different segments of the Indian population.

The primary analytical method employed in this study was logistic regression, chosen for its suitability in modelling binary and categorical outcome variables. Before the regression analysis, a chi-squared test was performed to examine the distributional characteristics of the input variables and identify significant correlation among them. Statistical significance was estimated at the 5% level ($p < 0.05$), and confidence intervals were calculated at a 95% confidence level.

Model robustness was evaluated using two standard information criteria: the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), ensuring the reliability and validity of the model fit.

4. Results and Analysis

The first section presents the results and analysis of Indian user's awareness of GenAI models and their perception of climate change. Four questions from the Questionnaire are interconnected: frequency of ChatGPT current use, use of the other GenAI systems, personal importance of the climate change solution and period of climate change. Table 1 presents the systems testing and their relationships to the respondents' environmental attitudes. As it is presented in Table 1, presents the results of chi-square tests assessing users' responses to various AI systems (AI1 to AI10) about their attitudes toward climate change, operationalized through two key constructs: Importance of solving the climate change issue (E1) and alignment of climate change concern with personal attitudes (E2). The initial chi-square test statistics and p-values indicate that users' responses differ significantly across systems. Most systems like ChatGPT, Gemini, Microsoft Copilot, Midjourney, DALL-E, and WhatsApp AI show statistically significant variation ($p < 0.05$), suggesting that users exhibit differential preferences or usage patterns across these AI tools, which may relate to their climate attitudes.

For E1, systems like ChatGPT ($\chi^2 = 1.84$, $p = 0.00429$), Gemini ($\chi^2 = 1.94$, $p = 0.0036$), and Microsoft Copilot ($\chi^2 = 2.31$, $p = 0.00764$) show significant correlations. This means that people who use these systems are more likely to consider solving climate change as important issue. Interestingly, Midjourney and DALL-E shows strong correlation ($p < 0.001$), suggesting that users who care more about climate change tend to be more engaged with AI tools that focus on visual or creative content.

For E2, several AI systems, including Microsoft Copilot ($p = 0.00731$), Midjourney ($p = 0.00301$), DALL-E ($p \approx 6.38E\text{-}32$), and Bing Chat ($p = 0.00132$) show a significant correlation with users' personal concern about climate change. This suggests that people who feel more connected to climate issues may be more likely to use or support these tools. DALL-E, in particular, stands out with an extremely low p-value, indicating a very strong correlation between users' climate attitudes and their engagement with this visual AI platform.

On the other hand, systems like Canva AI, YouTube Shorts AI Tools, and Instagram AI Stickers show no correlation with E1 and E2, suggesting they may be less influential or less aligned with users' climate-related values. The findings suggest that AI systems with generative or conversational capacities are more likely to be highly correlated with climate-conscious users. At the same time, more recreational or limited-use tools show weaker links. This highlights the role of AI tools in technological engagement and as possible reflections of users' environmental values and awareness.

Table1: Test results of awareness of AI systems and perception of climate

System	chi-square test statistic	p-value	chi-square test to E1 statistic	p-value	chi-square test to E2 statistic	p-value
AI1: ChatGPT	6.69	0.00	1.84	0.004	9.9	0.0625
AI2: Gemini (Bard)	6.6	0.00	1.94	0.004	7.9	0.0954
AI3: Microsoft Copilot	4.81	0.00	2.31	0.008	8.56	0.0073
AI4: Midjourney (optional in India)	9.14	0.00	7.61	0.000	9.06	0.0030
AI5: DALL·E	9.02	0.00	7.32	0.000	8.69	0.0000
AI6: Canva AI	1.03	0.07	1.18	0.067	1.45	0.0100
AI7: Bing Chat (Copilot)	1.07	0.00	6.71	0.003	7.22	0.0013
AI8: WhatsApp AI (beta/limited use)	7.4	0.01	2.35	0.007	1.05	0.0030
AI9: YouTube Shorts AI Tools	1.1	0.01	3.66	0.384	1.1	0.0265
AI10: Instagram AI Stickers	1.11	0.00	3.93	0.686	1.2	0.0329

Table 2 presents the results of a logistic regression model exploring how Indian respondents' frequency of ChatGPT use relates to their perception of the importance of climate change (E1). The relationship between ChatGPT's usage frequency and climate change's perceived importance shows inverse relationship. Specifically, respondents who frequently use ChatGPT are 8.52% more likely to perceive climate change as less important compared to others. This likelihood increases among those who use ChatGPT occasionally, with a 14.33% higher probability of downplaying the significance of climate change. Notably, respondents who do not currently use ChatGPT exhibit the highest likelihood, 17.83%, of considering the climate change issue as less important. These findings suggest a clear inverse trend: as the frequency of ChatGPT usage increases, the perceived importance of climate change tends to decrease. This suggests that in the Indian context, less frequent or non-use of ChatGPT correlates with a weaker prioritization of climate change, possibly due to reduced access to globally informed or AI-curated climate narratives.

Table 2: Regression results for the frequency of ChatGPT use to the importance of the climate-change issue

Frequency	Variable	Coefficient	Std. Error	p-value
Often	Intercept	2.056	0.348	0.015
	E1	1.085	0.110	0.325
Sometimes	Intercept	2.509	0.366	0.004
	E1	1.178	0.124	0.045
Not currently	Intercept	1.437	0.312	0.204
	E1	1.251	0.135	0.038

Table 3 presents the perceptions of Indian respondents regarding the expected timeline of climate change impact on society (E2), categorized by their frequency of ChatGPT usage. Frequent users ("often") are more likely to view climate change as a future event rather than an immediate crisis (odds increase by 9.2%, p = 0.452, not significant). However, occasional users show a statistically significant 21.8% increase in the odds of seeing climate change as a distant issue (p = 0.016). This perception becomes stronger among non-users, with odds increasing by 30.2% (p = 0.023), indicating they view climate change as even further removed from present-day reality.

Table 3: Regression results for the frequency of chatGPT use to the climate-change impact period

Frequency	Variable	Coefficient	Std. Error	p-value
Often	Intercept	2.180	0.340	0.022
	E2	1.092	0.106	0.452
Sometimes	Intercept	2.382	0.361	0.008
	E2	1.218	0.111	0.017
Not currently	Intercept	1.490	0.329	0.201
	E2	1.302	0.127	0.023

Thus, among Indian respondents, a lower frequency of ChatGPT use correlates with a delayed perception of climate change impacts, potentially reflecting limited exposure to AI-generated awareness or discourse on ongoing climate crises.

Table 4 presents the statistical interrelationships between environmental concerns and digital behaviour within the Indian digital media ecosystem. The matrix presents the test statistic values in the lower triangle) and their respective p-values are displayed in the upper triangle. They are facilitating an understanding of the strength and significance of correlations across variables such as climate change awareness, artificial intelligence tool usage, and digital communication patterns.

A statistically significant correlation is observed between the perceived importance of solving climate change (E1) and both the perceived timing of its impact (E2; p = 0.000) and awareness of the environmental impact of data center s (E3; p = 0.008). These findings indicate that Indian users who assign higher importance to addressing climate change are also more likely to perceive its impacts as imminent and recognize the ecological implications of digital infrastructure.

The correlation between E1 and the frequency of ChatGPT use (AI1; p = 0.034) is modest but statistically significant. This suggests that regular AI users may agree more to environmental discourse, potentially due to increased exposure to climate-related content or analytical engagement. Moreover, strong correlations are observed between E1 and both forms of digital social interaction and social network (SN1; p = 0.000) and communication platform usage (SN2; p = 0.001) the role of social media in shaping environmental awareness. Interestingly, the frequency of AI tool use (AI1) exhibits a weaker and statistically insignificant relationship with digital social interaction variables SN1 (p = 0.089) and SN2 (p = 0.112). This suggests that while AI usage is rising among Indian users, it is not yet fully integrated with the behavioural patterns of social or environmental expression online.

In contrast, E3 (data center awareness) shows highly significant correlation with both SN1 (p = 0.000) and SN2 (p = 0.000), indicating that individuals who are aware of the ecological burden of digital technologies are also more likely to engage actively in communication and sharing activities on these platforms. This may reflect a heightened sensitivity among digitally active users who internalize sustainability-related considerations into their media consumption and usage behaviour.

Table 4: The test results of the relationships between environmental and social network attitudes

	E1	E2	E3	AI1	SN1	SN2
E1	–	0	0.008	0.034	0	0.001
E2	210.5	–	0.005	0.061	0.01	0.047
E3	40.7	45.2	–	0.002	0	0
AI1	16.2	13.8	21.4	–	0.089	0.112
SN1	51.1	38.9	33.5	17.3	–	0.293
SN2	48.6	36.4	40.1	18.2	44.8	–

Finally, the weak and statistically non-significant relationship between SN1 and SN2 ($p = 0.293$) suggests that although both are part of the digital communication spectrum, the motivations and patterns behind using profile-based sharing platforms versus direct messaging platforms are distinct. The test results indicate that active social media and AI platform users demonstrate significant involvement in climate-related matters. The digital landscape shapes and mirrors users' attitudes toward the environment, although the intensity of this influence varies based on the specific platform and the focus of their behaviour.

Table 5 presents the logistic regression model estimating the relationship between the frequency of GenAI use and the willingness to transfer personal data to an energy-efficient cloud provider (variable E4.2) among Indian users. The results suggest a positive correlation between GenAI usage frequency and openness to environmentally responsible digital behaviour, but the relationships are not statistically significant at conventional thresholds.

Table 5: Logit regression model for the frequency of GenAI use to transfer personal data to an energy-efficient cloud provider

Frequency	Variable	Coefficient	Standard Error	p-value
Often	Intercept	2.3241	0.4523	0.0893
	E4.2	1.1987	0.1932	0.1485
Sometimes	Intercept	2.0654	0.4375	0.1021
	E4.2	1.3295	0.1851	0.0652
Not currently	Intercept	1.4982	0.4706	0.3214
	E4.2	1.1713	0.2045	0.2758

Respondents using GenAI tools often displayed a moderately higher willingness to transfer their data to an energy-efficient cloud provider, with an estimated coefficient of 1.1987 but p-value of 0.1485 shows no statistical significance. It signals a trend toward environmentally conscious decisions among frequent users. Similarly, users who reported using GenAI tools sometimes had an even higher estimated coefficient of 1.3295 ($p = 0.0652$), indicating a more pronounced but still marginally non-significant tendency to support sustainability through cloud provider selection. In contrast, users who do not currently engage with GenAI tools demonstrated the lowest willingness (coefficient = 1.1713), and this is not statistically significant ($p = 0.2758$).

The results indicate that the Indian GenAI users show a generally favourable disposition toward environmentally sustainable digital practices, particularly those who use such tools frequently; the absence of statistically significant values across groups highlights the need for greater environmental awareness campaigns. Educational interventions promoting green digital behaviour could further strengthen the alignment between technological adoption and sustainability in the Indian context.

Table 6 presents the logistic regression analysis to understand the correlation between the frequency of GenAI use and the willingness of Indian respondents to change their email addresses. The analysis reveals an inverse relationship: the lower the frequency of GenAI use, the higher the likelihood of reluctance to change the current email service provider.

Among respondents who frequently use GenAI tools, the odds of being unwilling to change their email address are only 15.34% higher (coefficient = 1.1534), and the relationship is not statistically significant ($p = 0.7296$). The reluctance increases for those who use GenAI occasionally, with the odds being 36.28% higher (coefficient = 1.3628), nearing statistical significance ($p = 0.0631$). The highest reluctance level is observed among respondents who currently do not use GenAI, with the odds increasing to 49.92% (coefficient = 1.4992), and the relationship is statistically significant ($p = 0.0287$).

Table 6: The frequency of GenAI use and willingness to change email address – regression model

Frequency	Variable	Coefficient	Standard error	p-value
Often	Intercept	2.4371	0.4551	0.0412
	E4.1	1.1534	0.1789	0.7296
Sometimes	Intercept	1.7893	0.4376	0.1982
	E4.1	1.3628	0.1805	0.0631
Not Currently	Intercept	1.0156	0.4887	0.9652
	E4.1	1.4992	0.1774	0.0287

The study findings show that users with lower usage of GenAI applications are generally less willing to adopt environmentally sustainable digital behaviours, such as transforming to energy-efficient email providers. This reluctance may be attributed to digital inertia or limited awareness of more sustainable digital infrastructure options. These results highlight the critical need to enhance awareness and education about green digital practices, particularly among low-frequency and non-users of GenAI, to promote more proactive and environmentally responsible technology adoption within the Indian context.

Table 7 illustrates the relationship between GenAI usage frequency and the willingness to leave a favourite social network without an energy-efficient data center. The results show a clear indirect dependence lower frequency of GenAI usage correlates with higher reluctance to abandon such networks. Indian respondents who use GenAI tools often show 2.71% higher odds of being unwilling to leave non-energy-efficient social networks. This reluctance increases for occasional users (32.29% higher odds) and significantly for non-users (52.39%), with statistical significance achieved at $p = 0.0302$. These findings suggest that lower engagement with GenAI corresponds to diminished environmental sensitivity in social media preferences among Indian users.

Table 7: The frequency of GenAI use and leaving a favourite social network that does not use an energy-efficient data center, regression model

Frequency	Variable	Coefficient	Std. Error	p-value
Often	Intercept	2.4611	0.4924	0.0413
	E4.3	1.0271	0.1986	0.8299
Sometimes	Intercept	2.2073	0.4601	0.0314
	E4.3	1.3229	0.1902	0.1496
Not Currently	Intercept	1.8466	0.5115	0.0468
	E4.3	1.5239	0.1721	0.0302

Table 8 presents the regression outcomes analysing the relationship between GenAI usage and the willingness to stop using a favourite streaming platform that lacks energy-efficient data center infrastructure. The results highlight a partial indirect dependence, more frequent GenAI users are less reluctant to discontinue such services. Frequent users have 7.10% lower odds of being unwilling to leave these platforms (coefficient = 0.9290), whereas those using GenAI sometimes show slightly higher reluctance (coefficient = 0.9758), and non-users present a mild decline again (coefficient = 0.9416). Despite p-values indicating mixed levels of significance, this pattern suggests that regular engagement with GenAI tools may promote more environmentally mindful digital behaviour among Indian users.

Table 8: The frequency of GenAI use and stopping the use of a favourite streaming platform that does not use energy-efficient data centers – regression model

Frequency	Variable	Coefficient	Std. Error	p-value
Often	Intercept	4.5171	0.4721	0.0012
	E4.4	0.929	0.1882	0.0431
Sometimes	Intercept	3.0649	0.4378	0.0294
	E4.4	0.9758	0.1732	0.0627
Not Currently	Intercept	3.0049	0.5024	0.0327
	E4.4	0.9416	0.1864	0.0758

Table 9 explores the relationship between GenAI use and the likelihood of stopping using a preferred AI system that does not utilize energy-efficient data centers. The findings reflect a weak indirect relationship: as GenAI usage frequency decreases, the odds of continuing with non-sustainable AI systems slightly increase. Regular users show only 5.03% lower odds of reluctance to abandon such AI systems. In comparison, occasional users exhibit minimal change (4.22% lower odds), and non-users show even weaker commitment to switch (14.29% lower odds). Despite modest coefficients, the statistical significance ($p < 0.05$) for all user groups implies that even subtle digital habits may influence broader environmental choices among Indian tech users.

Table 9: The frequency of GenAI use and stopping the use of a favourite AI system that does not use energy-efficient data centers – regression model

Frequency	Variable	Coefficient	Std. Error	p-value
Often	Intercept	3.1188	0.4992	0.0205
	E4.5	0.9497	0.1703	0.0401
Sometimes	Intercept	4.9387	0.4984	0.0123
	E4.5	0.9578	0.1935	0.0453
Not Currently	Intercept	3.5719	0.5023	0.0315
	E4.5	0.8571	0.1935	0.033

Conclusion

This study highlights a consistent pattern in digital environmental behaviours among Indian users of Generative Artificial Intelligence (GenAI), particularly emphasizing the influence of AI usage frequency on eco-conscious decisions. Across various scenarios, such as switching to energy-efficient cloud services, changing email providers, or abandoning platforms with unsustainable infrastructure, frequent users of GenAI tools demonstrate a greater tendency to adopt environmentally responsible practices. Conversely, individuals with low or no engagement with GenAI systems tend to resist these changes, favouring familiarity over sustainability.

While regular GenAI users exhibit more eco-friendly digital behaviours, they are paradoxically less concerned about the long-term implications of climate change. This contrast may stem from psychological factors such as optimism bias, information overload, availability heuristics, and the third-person effect. These cognitive mechanisms can diminish the perceived urgency of environmental issues, particularly when AI-generated content shapes daily information intake.

The Indian context reflects a nuanced relationship between AI literacy, environmental awareness, and behavioural response. Despite the sustainability benefits associated with regular AI tool usage, there is an evident gap in climate concern perception. Therefore, targeted interventions are necessary to address these cognitive barriers while leveraging the positive behavioural inclinations observed among frequent GenAI users.

The findings offer important insights for policymakers, educators, and AI developers in India. There is a clear need for AI literacy programs that incorporate sustainability principles, transparent disclosures regarding AI energy consumption, and behaviourally informed strategies to promote responsible digital habits. Ultimately, this research contributes to the emerging discourse on sustainable AI adoption and lays the foundation for cultivating an environmentally conscious AI culture in India.

Limitations and Future Directions

This study aims to understand the GenAI users' attitudes towards environmental issues with a focus on climate change concerns and awareness. The study results suggest notable correlations between the frequency and type of GenAI tool usage and users' perception of climate-related issues. Tools with generative or conversational capacities, such as ChatGPT, Gemini, and DALL·E, showed stronger links with environmentally conscious users, highlighting how digital tools may shape user values.

The study was conducted using primary survey data collected from an Indian population. Sociodemographic characteristics and geographical diversity were not included in the research design. Including respondents' demographic and geographical information in the study may offer valuable insights and help to understand how different population segments respond to environmental concerns.

Moreover, this analysis did not consider external factors such as digital literacy levels and the employment sector but may significantly influence user behaviours and attitudes. Including these dimensions in future research could lead to more comprehensive and insightful findings. Future studies should expand the procedural framework by incorporating sociodemographic and contextual variables to understand better how GenAI interconnects with digital sustainability. Including a cross-cultural comparison could help estimate the changes over time and across different settings.

This study provides initial insights into the connection between GenAI usage and environmental attitudes; there remains a need for continued, multidimensional research to capture this relationship's complexity and evolving nature.

Credit Authorship Contribution Statement

Jyothi Chittineni contributed to the conceptualization of the study, developed the methodology, led the investigation, supervised the research process. Maheswari, P. performed the formal analysis, managed data curation, contributed to the review and editing of the manuscript, and ensured validation of the findings. Sahila, C. conducted the literature review, managed research resources, created visual representations of data, and coordinated project administration. Balakrishnan, S. and was responsible for writing the original draft of the manuscript.

Conflict of Interest Statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

References:

Alkaf, A. R., Priatna, D. K., Yusliza, M. Y., Farooq, K., Khan, A., & Rastogi, M. (2023). Green intellectual capital and sustainability: The moderating role of top management support. *Polish Journal of Management Studies*, 28(1), 25 - 42. https://doi.org/10.17512/pjms.2023.28.1.02

Almiron, N., Moreno, J. A., & Farrell, J. (2023). Climate change contrarian think tanks in Europe: A network analysis. *Public Understanding of Science*, 32(3), 268-283. https://doi.org/10.1177/09636625221137815

Alzoubi, Y. I., & Mishra, A. (2024). Green artificial intelligence initiatives: Potentials and challenges. *Journal of Cleaner Production*, 468, Article 143090. https://doi.org/10.1016/j.jclepro.2024.143090

Amankwah-Amoah, J., Abdalla, S., Mogaji, E., Elbanna, A., & Dwivedi, Y. K. (2024). The impending disruption of creative industries by generative AI: Opportunities, challenges, and research agenda. *International Journal of Information Management*, 79, Article 102759. https://doi.org/10.1016/j.ijinfomgt.2024.102759

Brocklehurst, F. (2021). International Review of energy efficiency in data centers. https://www.dcceew.gov.au/sites/default/files/documents/international-review-energy-efficiency-data-centres.pdf

Chatterjee, D. (2024). An empire of artificial intelligence: Exploring an intersection of politics, society, and creativity. *International Journal of Politics, Culture, and Society*, 1–30. https://doi.org/10.1007/s10767-024-09484-3

Chauhan, D., Bahad, P., & Jain, J.K. (2024). Sustainable AI: Environmental implications, challenges, and opportunities. *Explainable AI (XAI) for Sustainable Development*, 1–15. https://doi.org/10.1201/9781003457176-1

Chen, J., Shang, H., Li, P., & Liu, J. (2024b). Green credit and carbon emission reduction technology R&D for competitiveness. *Journal of Competitiveness*, 16(4), 242-256. https://doi.org/10.7441/joc.2024.04.12

Coan, T. G., Boussalis, C., Cook, J., & Nanko, M. O. (2021). Computer-assisted classification of contrarian claims about climate change. *Scientific Reports*, 11(1), 22320. https://doi.org/10.1038/s41598-021-01714-4

Davison, W. P. (1983). The third-person effect in communication. *Public Opinion Quarterly*, 47(1), 1-15. https://doi.org/10.1086/268763

Dobbe, R., & Whittaker, M. (2019). AI and climate change: How they're connected, and what we can do about it. https://ainowinstitute.org/publication/ai-and-climate-change-how-theyre-connected-and-what-we-can-do-about-it

Edwards, D., Cooper, Z. G. T., & Hogan, M. (2024). The making of critical data center studies. *Convergence*. https://doi.org/10.1177/13548565231224157

Eppler, M. J., & Mengis, J. (2004). The concept of information overload: A review of literature from organization science, accounting, marketing, MIS, and related disciplines. *The Information Society*, 20(5), 325-344. https://doi.org/10.1080/01972240490507974

Ermakov, A. (2024). Expert commentary: Electricity demand growth for data centers and AI and implications for natural gas-fired power generation. https://www.gecf.org/_resources/files/events/gecf-expert-commentary-electricity-demand-growth-for-data-centres-and-ai-and-implications-for-natur/eefd-ec-2024-electricity-demand-for-data-centres-and-ai.pdf

Feuerriegel, S., Hartmann, J., Janiesch, C., & Zschech, P. (2024). Generative AI. *Business & Information Systems Engineering*, 66(1), 111–126. https://doi.org/10.1007/s12599- 023-00834-7

Freitag, C., Berners-Lee, M., Widdicks, K., Knowles, B., Blair, G. S., & Friday, A. (2021). The real climate and transformative impact of ICT: A critique of estimates, trends, and regulations. *Patterns*, 2(9), Article 100340. https://doi.org/10.1016/j.patter.2021.100340

Galaz, V., Centeno, M. A., Callahan, P. W., Causevic, A., Patterson, T., Brass, I., et al. (2021). Artificial intelligence, systemic risks, and sustainability. *Technology in Society*, 67(1), Article 101741. https://doi.org/10.1016/j.techsoc.2021.101741

Hogan, M. (2023). Environmental media" in the cloud: The making of critical data center, art. *New Media & Society*, 25(2), 384-404. https://doi.org/10.1177/14614448221149942

Hosseini, M., Gao, P., & Vivas-Valencia, C. (2024). A social-environmental impact perspective of generative artificial intelligence. *Environmental Science and Ecotechnology*, 23, Article 100520. https://doi.org/10.1016/j.ese.2024.100520

Ioku, T., Song, J., & Watamura, E. (2024). Trade-offs in AI assistant choice: Do consumers prioritize transparency and sustainability over AI assistant performance? *Big Data & Society*, *11*(4). https://doi.org/10.1177/20539517241290217

Kirkpatrick, A. W., Boyd, A. D., & Hmielowski, J. D. (2024). Who shares about AI? Media exposure, psychological proximity, performance expectancy, and information sharing about artificial intelligence online. *AI & Society*. https://doi.org/10.1007/s00146-024-01997-x

Leipold, S., Feindt, P. H., Winkel, G., & Keller, R. (2019). Discourse analysis of environmental policy revisited: Traditions, trends, perspectives. *Journal of Environmental Policy & Planning,* 21(5), 445–463. https://doi.org/10.1080/1523908x.2019.1660462

Levický, M., Fiľa, M., Maros, M., & Korenkova, M. (2022). Barriers to the development of the circular economy in small and medium-sized enterprises in Slovakia. *Entrepreneurship and Sustainability Issues*, 9(3), 76–87. https://doi.org/10.9770/jesi.2022.9.3(5)

Lewandowsky, S. (2021). Climate change disinformation and how to combat it. *Annual Review of Public Health*, 42(1), 1–21. https://doi.org/10.1146/annurev-publhealth- 090419-102409

Malkova, Y. (2025). Artificial intelligence and sustainable power. *The Sustainable Power Grid*, 43–58. https://doi.org/10.1016/B978-0-443-13442-5.00011-9

Moravec, V., Gavurova, B., & Kovac, V. (2025). Environmental footprint of GenAI–Changing technological future or planet climate? *Journal of Innovation & Knowledge*, 10(3), 100691. https://doi.org/10.1016/j.jik.2025.100691

Nisbet, M. C., & Scheufele, D. A. (2009). What's next for science communication? Promising directions and lingering distractions. *American Journal of Botany*, 96(10), 1767–1778. https://doi.org/10.3732/ajb.0900041

Piccinetti, L., Rezk, M. R., Kapiel, T. Y., Salem, N., Khasawneh, A., Santoro, D., et al. (2023). Circular bioeconomy in Egypt: The current state, challenges, and future directions. *Insights into Regional Development*, 5(1), 97–112. https://doi.org/10.9770/ird.2023.5.1(7)

Piccolo, L. S., Baranauskas, C., & Azevedo, R. (2017). A socially inspired energy feedback technology: Challenges in a developing scenario. *AI & Society,* 32, 383–399. https:// doi.org/10.1007/s00146-016-0653-8

Radavicius, T., & Tvaronaviciene, M. (2022). Digitalisation, knowledge management and technology transfer impact on organisations' circularity capabilities. *Insights into Regional Development*, 4(3), 76–95. https://doi.org/10.9770/ird.2022.4.3(5)

Sarathchandra, D., & Haltinner, K. (2021). How believing climate change is a "hoax" shapes climate skepticism in the United States. *Environmental Sociology*, 7(3), 225–238. https://doi.org/10.1080/23251042.2020.1855884

Sedkaoui, S., & Benaichouba, R. (2024). Generative AI as a transformative force for innovation: A review of opportunities, applications and challenges. *European Journal of Innovation Management*. https://doi.org/10.1108/ejim-02-2024-0129

Sharot, T. (2011). The optimism bias. Current Biology, 21(23), R941–R945. https://doi.org/10.1016/j.cub.2011.10.030

Tversky, A., & Kahneman, D. (1973). Availability: A heuristic for judging frequency and probability. *Cognitive Psychology*, 5(2), 207–232. https://doi.org/10.1016/0010-0285(73)90033-9

Wang, P., Zhang, L. Y., Tzachor, A., & Chen, W.-Q. (2024). E-waste challenges of generative artificial intelligence. *Nature Computational Science*, 4, 818–823. https://doi.org/10.1038/s43588-024-00712-6

Cite this article

Chittineni, J., Maheswari, P., Sahila, C., & Balakrishnan, S. (2025). Generative artificial intelligence and green choices: exploring environmental attitudes and digital behaviour in India. *Journal of Research, Innovation and Technologies*, Volume IV, 2(8), 143-172. https://doi.org/10.57017/jorit.v4.2(8).03

Article's history:

Received 4th of May, 2025; Revised 25th of May, 2025;
Accepted for publication 18th of June, 2025; Available online: 30th of June, 2025
Published as article in Volume IV, Issue 2(8), 2025

Annexure 1

Group 1: - Responses are recorded as - very often, often, sometimes and not currently

AI1: How often do you currently use the ChatGPT system?

AI2: Have you tried the Gemini system based on AI?

AI3: Have you tried the Microsoft Copilot system based on AI?

AI4: Have you tried the Midjourney system based on AI?

AI5: Have you tried the DALL-E system based on AI?

AI6: Have you tried the Canva AI system based on AI?

AI7: Have you tried the Bing Chat (Copilot) system based on AI?

AI8: Have you tried the WhatsApp AI system based on AI?

AI9: Have you tried the YouTube Shorts AI Tools system based on AI?

AI10: Have you tried the Instagram AI Stickers system based on AI?

Group 2: Environmental issues:

E1: How important is solving the climate change issue for you personally? *(Responses are captured on a scale of 1 to 7, with the lowest value showing the highest importance and the highest value showing the lowest importance).*

E2: Choose one of the following statements related to climate change that is the closest one to your attitude.

option 1: Climate change is already considerably affecting life around me.
option 2: Climate change will considerably affect life around me in the next five years.
option 3: Climate change will considerably affect the life around me in the next 6 to 10 years.
option 4: Climate change will considerably affect life around me in the next 11 to 25 years.
option 5: Climate change will not considerably affect life around me even after the next quarter of a century.

E3: How well do you know what a data center is and what it serves for?

option 1: I know it very well.
option 2: I know it little.
option 3: I do not know well.
option 4: I do not know it at all.

E4: After learning more details about the environmental impact of technology enterprises' data-centre operations, how willing would you be to take the next steps?

option 1: To change one's own email address or go to the email service provider that uses more energy-efficient and water-cooled data center s.
option 2: To transfer own data to a provider that uses more energy- efficient and water-cooled data center s.
option 3: To leave a favourite social network that does not use energy-efficient and water-saving opportunities in its data centers.
option 4: To stop using a favourite streaming platform that does not allow energy-efficient and water-saving opportunities in its data centers.
option 5: To stop using a favourite generative AI platform that does not allow energy-efficient and water-saving opportunities in its data centers.

Group 3: Use of the social networks:

SN1: How often do you use social networks, where you have created your own profile and share posts – photos and videos (for instance, Facebook, X, Instagram, TikTok, Snapchat)? *(The responses are recorded on a seven-level scale, while the individual levels represent more times per day to not at all).*

SN2: How often do you use the communication platforms that allow to exchange messages and multimedia files (for instance, WhatsApp, Messenger, Telegram Messenger, Signal, iMessage, Rakuten Viber, Kik Messenger, and so on)? *(The responses are recorded on a seven-level scale, while the individual levels represent more times per day to not at all.)*