Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 292 (2026) 6999–7007

Procedia Computer Science

www.elsevier.com/locate/procedia

30th International Conference on Knowledge-Based and Intelligent Information & Engineering Systems (KES 2026)

Who wants to use AI responsibly?

Predictors of intentions to limit unnecessary GenAI use

Karina Rutecka-Cicha[a], Paulina Rutecka-Cicha[b]*

[a]*Department of Communication Design and Analysis, University of Economics in Katowice, Bogucicka 3, 40-287 Katowice, Poland*
[b]*Department of Informatics, University of Economics in Katowice, Bogucicka 3, 40-287 Katowice, Poland*

Abstract

Generative AI (GenAI) tools are rapidly becoming part of everyday life, yet their environmental costs remain largely overlooked by users. This study investigates the psychological and behavioral predictors of intentions to limit unnecessary GenAI use among 500 Polish users. Hierarchical linear regression revealed that climate worry, AI environmental knowledge, self-assessed AI competence, and GenAI use frequency were all significant predictors, collectively explaining 23.8% of variance in limitation intentions. Contrary to expectations, more frequent GenAI use was associated with stronger — not weaker — intentions to limit use. The hypothesized moderating role of AI environmental knowledge in the relationship between climate worry and limitation intentions was not supported. Findings suggest that both environmental awareness and AI competence are relevant to responsible GenAI use, with implications for digital literacy.

© 2026 The Authors. Published by Elsevier B.V.
This is an open access article under the CC BY-NC-ND license (https://creativecommons.org/licenses/by-nc-nd/4.0)
Peer-review under responsibility of the scientific committee of the KES International Association

Keywords: generative AI; responsible AI use; climate worry; AI environmental knowledge; digital literacy;

1. Introduction

Generative artificial intelligence (GenAI) has become one of the fastest-spreading technologies in recent history. According to nationally representative survey data from the United States, by late 2024 45% of adults aged 18–64 were already using GenAI tools, and 27% of employed respondents had used them for work at least once in the previous week [1]. Over the following year, the adoption rate rose to 54.6%, indicating that GenAI is diffusing faster

* Corresponding author.
E-mail address: paulina.rutecka-cicha@uekat.pl

1877-0509 © 2026 The Authors. Published by Elsevier B.V.
This is an open access article under the CC BY-NC-ND license (https://creativecommons.org/licenses/by-nc-nd/4.0)
Peer-review under responsibility of the scientific committee of the KES International Association

than personal computers or the internet did at a comparable stage of development [2]. Tools such as ChatGPT, Gemini, and Copilot are now widely used for writing, translation, data analysis, and problem-solving across both professional and personal contexts.

This rapid growth, however, is accompanied by growing concern about the environmental costs of GenAI. The carbon footprint of AI systems is estimated to reach between 32.6 and 79.7 million tons of CO_2 emissions in 2025, while the water consumption of the data centers supporting them may reach 312.5–764.6 billion liters [3]. According to projections by the International Energy Agency, global electricity demand from data centers could more than double by 2030, reaching approximately 945 terawatt-hours [4]. Despite growing scientific and media attention to this issue, public awareness of the environmental costs of GenAI remains low — research points to a clear gap between the availability of information and users' actual knowledge levels [5].

Climate worry alone, however, may not be sufficient to motivate users to limit their unnecessary GenAI use. Research in environmental psychology suggests that translating environmental concern into concrete behavioral intentions requires additional cognitive and behavioral factors [6]. Knowledge of the ecological costs of technology may strengthen the willingness to limit its use [7], [8], yet knowledge does not always translate into action. User competence in AI may moderate the capacity for conscious self-regulation of technology use [9], while GenAI usage habits may both impede and — paradoxically — facilitate reflection on limiting use [10].

Despite growing interest in the environmental dimensions of AI, empirical research identifying the psychological and behavioral predictors of willingness to limit unnecessary GenAI use remains scarce. Existing work focuses primarily on the environmental costs of the technology itself [3] or on users' broad pro-environmental attitudes [11], [12], without directly addressing the question of who is willing to use AI more responsibly and what drives that willingness.

In light of the environmental costs associated with GenAI, the aim of this study is to identify the psychological and behavioral predictors of intentions to limit unnecessary generative AI use. For the purposes of this study, unnecessary GenAI use is operationally defined as use driven by convenience or habit rather than genuine task need. Drawing on a review of the literature, five hypotheses were formulated: higher climate worry (H1) and higher environmental knowledge about AI (H2) are associated with stronger limitation intentions; more frequent GenAI use is associated with weaker limitation intentions (H3); self-assessed AI competence is related to limitation intentions, with the direction of this relationship treated as exploratory (H4); and environmental knowledge about AI moderates the relationship between climate worry and limitation intentions (H5).

The article is organized as follows. The Theoretical Framework section reviews the psychological and behavioral foundations of the hypotheses. The Methods section describes the study procedure and measures. The Results section presents the statistical findings. The Discussion interprets the results in relation to the literature, and the article closes with a Conclusions section summarizing the main findings, study limitations, and directions for future research.

2. Theoretical Framework

2.1. Climate worry

Climate worry refers to an emotional response to the threats associated with climate change, encompassing feelings of anxiety, concern, and a sense of urgency [13]. In the psychological literature, climate worry is treated as an important motivator of pro-environmental behavior — individuals who are more concerned about climate change show greater willingness to take actions that reduce CO_2 emissions, such as limiting energy consumption or changing consumption habits. The same body of research indicates that the strength of this relationship may be moderated by cognitive factors, such as expectations regarding the effectiveness of one's own actions [6].

In the context of digital technologies, climate worry takes on new relevance alongside growing awareness of the environmental costs of AI systems [14]. Generative AI involves substantial electricity and water consumption, making it a potential target of pro-environmental behavioral self-regulation [12]. Khalufi [15] argues that environmental concern acts as a psychological catalyst that transforms ecological awareness into concrete behavioral intentions. Research also shows that more frequent GenAI users tend to perceive climate change as more temporally distant and less urgent, indirectly suggesting that climate worry may serve as a natural regulator of the intensity of GenAI use [11]. On this basis, the following hypothesis was formulated:

H1. Higher climate worry is associated with stronger intentions to limit unnecessary GenAI use.

2.2. Environmental knowledge about AI

Environmental knowledge is defined as an individual's stock of information about the natural environment, its threats, and the consequences of human actions for ecosystems [12]. It is also regarded as one of the key cognitive predictors of pro-environmental behavior — individuals with greater knowledge of the consequences of their actions are assumed to be more likely to modify them [7], [8]. In relation to digital technologies, environmental knowledge about AI encompasses awareness of phenomena such as the energy intensity of language models, water consumption in data centers, and CO_2 emissions associated with training and operating GenAI systems.

Research nonetheless points to a gap between knowledge and action — awareness of the ecological costs of AI does not always translate into behavioral change [5]. Scholars emphasize that ecological awareness and experience are key determinants of GenAI adoption for sustainable development purposes [16], while others show that the cognitive components of ecological awareness are key determinants of pro-environmental behavioral intentions in the context of AI use [8]. On this basis, the following hypothesis was formulated:

H2. Higher environmental knowledge about AI is associated with stronger intentions to limit unnecessary GenAI use.

2.3. Frequency of GenAI use

The frequency of digital technology use is treated in the literature as an ambiguous predictor of intentions to limit that use. On the one hand, research indicates that more intensive GenAI use promotes habit formation and behavioral dependency, which undermines the capacity for conscious self-regulation [17]. More frequent ChatGPT use has also been linked to higher levels of AI dependency, which may result in reduced self-control and weaker intentions to limit use [18]. Other researchers confirm that perceived dependency on GenAI varies significantly by average daily usage time [19]. On the other hand, there are suggestions that when GenAI use becomes automatic and routine, it may lead to digital fatigue and reduced critical engagement with the technology [10]. Based on the dominant strand of the literature, the following hypothesis was formulated:

H3. More frequent GenAI use is associated with weaker intentions to limit unnecessary use.

2.4. Self-assessed AI competence

Self-assessed AI competence refers to a subjective evaluation of one's own skills in using AI systems, understanding their functioning, and critically evaluating their outputs. In the literature, digital competence is treated as a factor that facilitates conscious and reflective technology use — individuals with higher competence more frequently engage in active regulation of their own technological behavior [9]. Researchers also identify perceived competence as a key element of self-efficacy in the domain of AI, which in a staged model leads from repeated use to competence gains and potential dependency on the technology [20].

The relationship between competence and intentions to limit use is not, however, straightforward. Kherismawati and Suandana [21] document the phenomenon of the illusion of competence — intensive GenAI use may generate high self-assessments without real skill development. Al-Obaydi and Pikhart [9] by contrast, find that high self-efficacy is associated with lower susceptibility to AI dependency and greater capacity for self-regulation. Given this theoretical ambiguity, an exploratory hypothesis was formulated:

H4. Self-assessed AI competence will be related to intentions to limit unnecessary GenAI use, although the direction of this relationship is not predicted in advance.

2.5. The moderating role of environmental knowledge

The moderating role of knowledge in the relationship between environmental concern and pro-environmental behavior is relatively underexplored, particularly in the context of digital technologies. Ellahi [22] suggests that ecological sensitivity and environmental motivation are likely moderating variables for the outcomes of GenAI-based

educational interventions. ICT proficiency has been shown to moderate the relationship between climate anxiety and expectations about extreme weather events, suggesting that digital skills may serve as a bridge between emotional concern and cognitive representations of climate risk [23]. Van Laarhoven [5] emphasizes that practical knowledge of how to act pro-environmentally is a factor that enables the translation of general awareness and intention into concrete action. On this basis, the following hypothesis was formulated:

H5. Environmental knowledge about AI will moderate the relationship between climate worry and intentions to limit unnecessary GenAI use, such that the positive association will be stronger among respondents with higher knowledge.

3. Methods

The study was conducted between February 26 and March 23, 2026, using the Polish online research panel SW Research and the CAWI method. Of the 737 adult respondents who initially completed the survey, 216 were excluded for reporting no prior use of generative AI tools, and a further eight cases were removed due to very small gender categories that precluded reliable subgroup analyses. Incomplete responses were also excluded. The final sample consisted of 500 generative AI users from Poland, comprising 302 women (60.4%) and 198 men (39.6%). The largest age group was 30–45 years (42.4%), followed by 18–29 years (26.8%). In terms of education, the most common qualifications were a master's degree or equivalent (27.2%) and technical secondary or post-secondary education (25.4%). Participants most often lived in medium-sized cities (26.6%) and were employed full-time (49.4%). The survey was anonymous and voluntary, and respondents could withdraw at any point.

Intentions to limit unnecessary GenAI use were measured with three items assessing willingness to reduce convenience-based use, minimize excessive prompting, and avoid unnecessarily long AI-generated outputs. Responses were averaged into a composite score, with higher values indicating stronger intentions to limit unnecessary use (Cronbach's $\alpha = .83$). Both the limitation intentions scale and the AI competence scale were developed specifically for this study on the basis of a review of the responsible AI use literature and validated in a pilot study conducted prior to the main data collection. Climate worry was assessed using the 10-item Climate Change Worry Scale [24] (Cronbach's $\alpha = .949$ in the present sample), with higher mean scores indicating greater concern about climate change. AI environmental knowledge was measured with a seven-item factual test covering energy use, water consumption, and the environmental impact of training AI models, with correct responses summed into an overall knowledge score (range: 0–7). As a factual knowledge test rather than a reflective self-report scale, internal consistency is not a standard psychometric requirement for this measure. Self-assessed AI competence was measured with a multi-item scale assessing confidence, critical evaluation skills, and perceived ability to use generative AI effectively, with higher values reflecting greater perceived competence (Cronbach's $\alpha = .741$). Additional variables included self-rated computer skills, frequency of GenAI use during the previous 30 days, age, gender, and education level.

Data were analyzed using IBM SPSS Statistics 29. Descriptive statistics and Spearman correlations were calculated for all variables. To test H1–H4, a hierarchical linear regression was conducted with intentions to limit unnecessary GenAI use as the dependent variable, with demographic variables entered in Block 1 and main predictors in Block 2. To test H5, a moderation analysis was conducted using the PROCESS macro [25], with climate worry as the predictor, AI environmental knowledge as the moderator, and demographic and behavioral variables as covariates. Variables entering the interaction term were mean-centered prior to analysis.

4. Results

This section presents the results of the statistical analyses conducted to test the hypotheses, including descriptive statistics, correlation analysis, and hierarchical linear regression.

Descriptive statistics and correlations are presented in Table 1. Respondents reported moderate levels of GenAI use ($M = 3.10$, $SD = 1.75$) and above-midpoint self-assessed AI competence ($M = 4.63$, $SD = 1.07$). Climate worry was moderate ($M = 2.70$, $SD = 1.11$), while scores on the AI environmental knowledge test were relatively low ($M = 2.41$ out of 7, $SD = 1.84$), indicating limited awareness of the ecological costs of AI systems. Mean intentions to limit unnecessary GenAI use were moderately high ($M = 4.54$, $SD = 1.40$).

Rho-Spearman correlation analyses revealed several statistically significant associations that provide preliminary support for a number of the hypotheses. Intentions to limit unnecessary GenAI use were positively correlated with climate worry ($r = .26$, $p < .01$), consistent with H1, suggesting that individuals more concerned about climate change expressed stronger intentions to limit AI use. A significant positive association was also found between self-assessed AI competence and limitation intentions ($r = .32$, $p < .01$) — individuals who perceived themselves as more competent AI users expressed greater willingness to limit unnecessary use, which is relevant to the exploratory H4.

Table 1. Descriptive statistics and correlations among study variables (Spearman's rho, n = 500)

Variable	1	2	3	4	5	6	7	8	M	SD
1. Gender	—								—	—
2. Age	.015	—							—	—
3. Education	-.151**	.278**	—						—	—
4. Computer skills	.064	-.079	.164**	—					5.26	1.21
5. GenAI use frequency	-.039	.028	-.051	-.153**	—				3.10	1.75
6. Climate worry	-.013	.096*	-.009	−.002	-.057	—			2.70	1.11
7. AI competence	-.014	-.039	.141**	.341**	-.331**	.082	—		4.63	1.07
8. AI use limitation intentions	-.129**	.061	.130**	.094*	.058	.261**	.320**	—	4.54	1.40
9. AI environmental knowledge	.054	-.123**	.047	.115*	-.175**	.216**	.190**	.195**	2.41	1.84

Note. Gender was coded dichotomously (1 = male, 2 = female). All variables were measured on a 1–7 scale, except Climate worry (1–5) and AI environmental knowledge (0–7 correct answers). Correlations significant p < .05, *p < .01.*

Higher education level was weakly but significantly associated with stronger limitation intentions ($r = .13$, $p < .01$), as were self-rated computer skills ($r = .09$, $p < .05$). AI environmental knowledge also showed a significant positive association with limitation intentions ($r = .20$, $p < .01$), providing preliminary support for H2 and suggesting that individuals more familiar with the ecological costs of AI systems expressed stronger intentions to limit their use. Gender was negatively associated with limitation intentions ($r = −.13$, $p < .01$), with women reporting lower intentions. Frequency of GenAI use did not show a significant association with limitation intentions ($r = .06$, $p = .198$), offering no preliminary support for H3.

To test H1–H4, a hierarchical linear regression was conducted with intentions to limit unnecessary GenAI use as the dependent variable. Demographic variables (gender, age, education) were entered in Block 1, and main predictors (self-assessed AI competence, climate worry, AI environmental knowledge, GenAI use frequency) in Block 2. Prior to analysis, regression assumptions and the presence of outliers were examined — a small number of cases (n = 11) with low values on the dependent variable were identified but retained in the analyses given the mild nature of the deviations and the large sample size (N = 500). No violations of normality of residuals, homoscedasticity, or multicollinearity were found (all VIF < 1.17). Results are presented in Table 2.

The control variables entered in Block 1 explained 3.9% of the variance in limitation intentions ($R^2 = .039$, $F(3, 496) = 6.70$, $p < .001$), with a significant effect emerging only for gender ($\beta = −.130$, $p = .004$) — women reported lower limitation intentions.

The introduction of the main predictors in Block 2 significantly increased the explained variance ($\Delta R^2 = .200$, $p < .001$), and the final model explained 23.8% of the variance in the dependent variable ($R^2 = .238$). Among the main predictors, the strongest effect was found for self-assessed AI competence ($\beta = .344$, $p < .001$) — individuals who perceived themselves as more competent AI users expressed stronger intentions to limit unnecessary use, providing support for the exploratory H4. Climate worry was also a significant predictor of limitation intentions ($\beta = .205$, $p < .001$), confirming H1. AI environmental knowledge emerged as a significant predictor ($\beta = .126$, $p = .003$), supporting H2. A surprising finding was the effect of GenAI use frequency ($\beta = .222$, $p < .001$) — contrary to H3, more frequent GenAI use was associated with stronger, not weaker, limitation intentions.

Table 2. Hierarchical linear regression predicting intentions to limit unnecessary GenAI use (N = 500)

Predictor	Block 1			Block 2		
	B	***SE***	***β***	***B***	***SE***	***β***
Control variables						
Gender	−.372	.128	−.130**	−.354	.115	−.123**
Age	.076	.069	.051	.083	.063	.055
Education	.099	.042	.110*	.056	.038	.062
Main predictors						
AI competence	—	—	—	.448	.056	.344***
Climate worry	—	—	—	.259	.052	.205***
AI environmental knowledge	—	—	—	.096	.032	.126**
GenAI use frequency	—	—	—	.178	.034	.222***
Moderation (H5)						
Climate worry × AI knowledge	—	—	—	.014	.029	—
R^2	.039			.239		
Adjusted R^2	.033			.226		
ΔR^2	.039***			.200***		
F	6.700***			19.235***		

Note. Gender coded dichotomously (1 = male, 2 = female). AI environmental knowledge scored 0–7. Block 3 tests the moderation hypothesis (H5): the interaction term Climate worry × AI knowledge was not statistically significant. Variables entering the interaction term were mean-centered prior to analysis. VIF values ranged from 1.028 to 1.165. Durbin-Watson = 2.00.
** $p < .05$. ** $p < .01$. *** $p < .001$.*

To test H5, a moderation analysis was conducted using the PROCESS macro [25], with climate worry as the predictor (X), AI environmental knowledge as the moderator (W), and intentions to limit GenAI use as the dependent variable (Y). Gender, age, education, self-assessed AI competence, and GenAI use frequency were included as covariates. Variables entering the interaction term were mean-centered prior to analysis. The interaction effect was not statistically significant (b = .014, SE = .029, t = .482, p = .630, ΔR^2 = .0004), thus H5 was not supported. AI environmental knowledge does not moderate the relationship between climate worry and intentions to limit AI use.

5. Discussion

The aim of this study was to examine the predictors of intentions to limit unnecessary use of GenAI tools. The findings partially support the hypotheses and offer new insights into the psychological and behavioral determinants of responsible AI use.

In line with H1, climate worry emerged as a significant predictor of intentions to limit GenAI use (β = .206, $p <$ .001). This finding is consistent with research showing that environmental concern fosters pro-environmental behavioral intentions [6], [13], and that concerns about the climate-related consequences of AI are associated with lower GenAI adoption [26]. Individuals more worried about climate change may perceive limiting AI use as one available means of reducing their carbon footprint, particularly given growing awareness of the energy intensity of GenAI systems [12], [14].

H2 was also supported — AI environmental knowledge significantly predicted limitation intentions (β = .126, p = .003). This finding is consistent with earlier research showing that awareness of the ecological costs of digital technologies translates into pro-environmental behavioral intentions [7], [8]. It is worth noting, however, that the effect of knowledge was relatively weak, which is consistent with the documented knowledge-action gap — some

research shows that awareness of the environmental consequences of GenAI does not always lead to actual behavioral change [5].

Contrary to H3, GenAI use frequency was associated with stronger, not weaker, limitation intentions ($\beta = .223$, $p < .001$). This finding is paradoxical in light of research suggesting that more frequent GenAI use promotes behavioral dependency and undermines control over one's technology use [17], [18]. It can, however, be interpreted in two ways. First, individuals who regularly use GenAI may be more aware of the scale of their own use, which may prompt reflection on limiting it — an effect consistent with the observation by Sabani et al. [10] that habitual use can lead to digital fatigue. Second, it is possible that the declared intentions do not translate into actual behavior, which is consistent with the well-documented intention-behavior gap [27]. Both interpretations remain speculative, and the directionality of this relationship cannot be established from cross-sectional data. Longitudinal or experimental designs would be needed to determine whether higher use frequency promotes reflective self-regulation or whether the observed association is primarily an artifact of inflated self-reported intentions.

Self-assessed AI competence emerged as the strongest predictor of limitation intentions ($\beta = .344$, $p < .001$), providing support for the exploratory H4. Al-Obaydi and Pikhart [9] found that higher self-efficacy is associated with lower AI dependency and greater capacity for self-regulation, which is consistent with the present finding. At the same time, Kherismawati and Suandana [21] suggest that high self-assessment may be an artifact of intensive use rather than genuine skill. An alternative interpretation is therefore possible: individuals with higher self-assessed AI competence may express stronger limitation intentions not because they better understand the technology, but because they feel sufficiently competent to consciously decide when to use it and when not to.

H5 was not empirically supported ($b = .014$, $SE = .029$, $p = .630$, $\Delta R^2 = .0004$). AI environmental knowledge does not moderate the relationship between climate worry and limitation intentions. The absence of a moderation effect may reflect the generally low level of AI environmental knowledge in the sample ($M = 2.41/7$), which may have limited the variance of the moderator and the statistical power to detect an interaction. It is also possible that climate worry and environmental knowledge operate as independent, additive predictors of intentions rather than mutually reinforcing factors — a conclusion supported by the significant main effects of both variables in the regression model.

6. Conclusions

This study aimed to identify the predictors of intentions to limit unnecessary generative AI use. The analyses revealed that climate worry (H1), AI environmental knowledge (H2), and self-assessed AI competence (H4) are significant predictors of stronger limitation intentions. Contrary to H3, however, GenAI use frequency was associated with stronger rather than weaker intentions. No moderation of the climate worry–limitation intentions relationship by AI environmental knowledge was observed (H5). Collectively, the predictors included in the model explained 23.8% of the variance in the dependent variable, a result comparable to other cross-sectional studies of self-report-based technology behaviors.

The findings carry several practical implications. They suggest that educational campaigns increasing awareness of the ecological costs of AI systems may promote more responsible GenAI use. The fact that self-assessed AI competence is the strongest predictor of limitation intentions further suggests that programs developing conscious and critical AI use [28], [29] may be more effective for promoting responsible use than environmental appeals alone. Relevant examples include competency-based AI literacy curricula aligned with frameworks such as those proposed by UNESCO [30], as well as targeted interventions that embed environmental cost feedback directly into GenAI interfaces — such as displaying estimated energy or carbon cost alongside generated outputs.

The study has, however, several limitations. The cross-sectional design precludes causal inference, and the self-report measurement of intentions introduces at least two additional limitations. First, declared intentions may be inflated due to social desirability bias, particularly given the normative connotations of responsible AI use. Second, , intentions are an imperfect proxy for behavior: the intention–behavior gap is well documented in the environmental domain [27], and it remains unclear whether respondents who expressed stronger intentions to limit GenAI use would follow through in practice. Although large ($N = 500$), the sample was drawn from a single country and may not be representative of GenAI users more broadly. Additionally, occupational profile was not systematically assessed — only employment status was recorded (e.g., full-time employed, student, unemployed). Factors such as field of work or degree of exposure to AI-related tasks were therefore not controlled for, and may represent potential confounders

— particularly in relation to self-assessed AI competence. The low mean level of AI environmental knowledge (M = 2.41/7) may also have limited the statistical power to detect the moderation effect in H5.

Future research should employ a longitudinal design to assess whether intentions translate into actual behavioral change over time. It would also be valuable to examine whether educational interventions increasing AI environmental knowledge can strengthen the effect of climate worry on limitation intentions — which would constitute an experimental test of the unsupported H5. Including a broader range of potential moderators, such as subjective norms and perceived self-efficacy, as well as replication in samples from other countries, would contribute to a fuller understanding of the determinants of responsible GenAI use.

References

[1] A. Bick, A. Blandin, D. Deming, N. Fuchs-Schündeln, and J. Jessen, "Mind the Gap: AI Adoption in Europe and the U.S.," Mar. 2026. doi: 10.3386/w34995.

[2] A. Bick, A. Blandin, and D. Deming, "The Rapid Adoption of Generative AI," Cambridge, MA, Sep. 2024. doi: 10.3386/w32966.

[3] A. de Vries-Gao, "The carbon and water footprints of data centers and what this could mean for artificial intelligence," *Patterns*, vol. 7, no. 1, p. 101430, Jan. 2026, doi: 10.1016/j.patter.2025.101430.

[4] International Energy Agency, "Electricity 2024: Analysis and forecast to 2026," 2024.

[5] A. van Laarhoven, "Embedding environmental sustainability in GenAI usage: A design science approach to explore interventions for sustainable GenAI interaction," Delft University of Technology, 2025. [Online]. Available: https://repository.tudelft.nl/file/File_2ba555e7-a1fc-4843-8825-5b036b71d45f

[6] T. Gregersen, R. Doran, G. Böhm, and W. Poortinga, "Outcome expectancies moderate the association between worry about climate change and personal energy-saving behaviors," *PLoS One*, vol. 16, no. 5, p. e0252105, May 2021, doi: 10.1371/journal.pone.0252105.

[7] Z. Barnett-Itzhaki and A. Tsoury, "From Awareness to Action: A UK-Based Study on Public Perceptions of Digital Pollution," *Sustainability*, vol. 17, no. 17, p. 7839, Aug. 2025, doi: 10.3390/su17177839.

[8] D. Jelonek and I. Pawełoszek, "Attitudes and digital choices of society towards the green AI trend," *Econ. Environ.*, vol. 96, no. 1, p. 1160, Mar. 2026, doi: 10.34659/eis.2026.96.1.1160.

[9] L. H. Al-Obaydi and M. Pikhart, "Artificial intelligence addiction: exploring the emerging phenomenon of addiction in the AI age," *AI Soc.*, vol. 41, no. 2, pp. 1577–1593, Feb. 2026, doi: 10.1007/s00146-025-02535-z.

[10] A. Sabani, H. G. Nguyen, D. Le, and M. Farah, "Unlocking students' continuance intention to use generative AI for educational purposes: the dual role of habit," *J. Trade Sci.*, vol. 14, no. 1, pp. 4–24, Mar. 2026, doi: 10.1108/JTS-08-2025-0038.

[11] S. Balakrishan, J. Chittiineni, P. Maheswari, and C. Sahila, "Generative Artificial Intelligence and Green Choices: Exploring Environmental Attitudes and Digital Behaviour in India," *J. Res. Innov. Technol.*, vol. 4, no. 16, p. 159, Jun. 2025, doi: 10.57017/jorit.v4.2(8).03.

[12] A. Laachach and N. Sadiku-Dushi, "Generative AI and Environmental Sustainability: Behavioral Mediation and Carbon Footprint Challenges," *Bus. Strateg. Environ.*, Feb. 2026, doi: 10.1002/bse.70651.

[13] E.-L. Sundblad, A. Biel, and T. Gärling, "Intention to change activities that reduce carbon dioxide emissions related to worry about global climate change consequences," *Eur. Rev. Appl. Psychol.*, vol. 64, no. 1, pp. 13–17, Jan. 2014, doi: 10.1016/j.erap.2011.12.001.

[14] N. Onel, L. Elgaaied-Gambier, S. Baskentli, and E. Van Tonder, "From algorithms to ecosystems: A transformative consumer research perspective on artificial intelligence for sustainable living," *AMS Rev.*, vol. 15, no. 3–4, pp. 390–415, Dec. 2025, doi: 10.1007/s13162-025-00308-x.

[15] N. A. M. Khalufi, "Digital Nudges and Environmental Concern in Shaping Sustainable Consumer Behavior Aligned with SDGs 12 and 13," *Sustainability*, vol. 17, no. 24, p. 11292, Dec. 2025, doi: 10.3390/su172411292.

[16] S. S. Hevi, G. Nkrumah, E. Asiedu, C. D. Agbenorxevi, and E. Malcalm, "Generative-AI and sustainable innovation among artisanal firms in the extractive industry: does evolutionary sense-making and pro-environmental behavior matter?," *Technol. Sustain.*, vol. 4, no. 3, pp. 199–213, Sep. 2025, doi: 10.1108/TECHS-01-2025-0001.

[17] J. Liu, "When Usefulness Fuels Fear: The Paradox of Generative AI Dependence and the Mitigating Role of AI Literacy," *Int. J. Human–Computer Interact.*, vol. 42, no. 7, pp. 5265–5286, Apr. 2026, doi: 10.1080/10447318.2025.2544006.

[18] M. Abbas, T. I. Khan, and F. A. Jam, "Avoid Excessive Usage: Examining the Motivations and Outcomes of Generative Artificial Intelligence Usage among Students," *J. Acad. Ethics*, vol. 23, no. 4, pp. 2423–2442, Dec. 2025, doi: 10.1007/s10805-025-09659-3.

[19] O. Robayo-Pinzon, S. Rojas-Berrio, J. E. Camargo, and G. R. Foxall, "Generative artificial intelligence (GenAI) use and dependence: an approach from behavioral economics," *Front. Public Heal.*, vol. 13, Aug. 2025, doi: 10.3389/fpubh.2025.1634121.

[20] A. M. Kalimira and K. Jazayeri, "From Social Drivers to Sustainable AI Usage and Dependency in Higher Education: Roles of Trust, Perceived Competence, and Perceived Intelligence," *Sustainability*, vol. 18, no. 3, p. 1598, Feb. 2026, doi: 10.3390/su18031598.

[21] N. P. E. Kherismawati and N. P. W. Suandana, "Artificial competence: The impact of generative AI dependency on students' critical thinking and problem-solving agility," *TECHNOVATE J. Inf. Technol. Strateg. Innov. Manag.*, vol. 2, no. 4, 2025, [Online]. Available: https://www.globalresearcher.net/index.php/technovate/article/view/186

[22] H. Ellahi, “Leveraging generative AI for environmental education: Effects on students’ environmental knowledge and attitudes with moderating influence of ecological susceptibility,” *Digit. Soc. Rev.*, vol. 1, no. 1, 2026.

[23] N. Alfirević, Z. Klepić, and M. Mihaljević Kosor, “ICT Proficiency as a Moderator of Climate Concern and Extreme Weather Expectations Among University Students of Business and Economics,” *Sustainability*, vol. 17, no. 11, p. 4840, May 2025, doi: 10.3390/su17114840.

[24] A. E. Stewart, “Psychometric Properties of the Climate Change Worry Scale,” *Int. J. Environ. Res. Public Health*, vol. 18, no. 2, p. 494, Jan. 2021, doi: 10.3390/ijerph18020494.

[25] A. F. Hayes, *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach*, 3rd editio. New York, NY, USA: Guilford Press, 2022.

[26] F. Stephany and J. Duszynski, “Women Worry, Men Adopt: How Gendered Perceptions Shape the Use of Generative AI,” Jan. 2026, [Online]. Available: http://arxiv.org/abs/2601.03880

[27] P. Sheeran and T. L. Webb, “The Intention–Behavior Gap,” *Soc. Personal. Psychol. Compass*, vol. 10, no. 9, pp. 503–518, Sep. 2016, doi: 10.1111/spc3.12265.

[28] C. Chedrawi, G. Haddad, A. Tarhini, S. Osta, and N. Kazoun, “Exploring the impact of responsible AI usage on users’ behavioral intentions,” *J. Innov. Knowl.*, vol. 10, no. 6, p. 100813, Nov. 2025, doi: 10.1016/j.jik.2025.100813.

[29] E. Papagiannidis, P. Mikalef, and K. Conboy, “Responsible artificial intelligence governance: A review and research framework,” *J. Strateg. Inf. Syst.*, vol. 34, no. 2, p. 101885, Jun. 2025, doi: 10.1016/j.jsis.2024.101885.

[30] “Guidance for generative AI in education and research,” UNESCO, 2023. doi: 10.54675/EWZM9535.