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Exploring the Associations Between Socioeconomic and Demographic Factors and Literacy in Environmental and Digital Pollution

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Abstract

The widespread integration of digital technologies into the industry, institutions, and everyday life has introduced environmental challenges known as digital pollution, including the carbon footprint of data centers, energy consumption of digital devices, and electronic waste (e-waste). While general environmental education is extensively studied, public awareness and understanding of digital pollution remain overlooked. This study investigates how demographic factors, including age, education level, income, and occupation, in addition to the perception of environmental knowledge and self-assessed tech-savviness, are associated with environmental and digital pollution literacy. A cross-sectional survey of 300 participants from the UK was conducted, assessing the associations between demographic characteristics, environmental knowledge, and digital pollution awareness. The findings reveal that education level and income are not significantly correlated with literacy scores, whereas age and tech-savviness display meaningful associations with digital pollution literacy. Additionally, general environmental knowledge is positively correlated with digital pollution literacy, suggesting that enhancing environmental literacy may foster a deeper understanding of digital sustainability issues. Notably, a gap emerged between self-reported and actual knowledge, highlighting the need for educational interventions. These findings suggest practical implications for developing targeted educational programs and policies that promote sustainable digital practices and reduce environmental impacts.

Keywords: digital pollution literacy; environmental awareness; digital sustainability; data center impact; environmental education; public environmental knowledge

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1. Introduction

The rapid advancement of digital technologies has profoundly transformed modern society, bringing numerous benefits to industry, education, and the economy. However, it has also introduced significant environmental challenges, collectively referred to as "digital pollution." Digital pollution encompasses various environmental impacts arising from digital technologies. Recent research has shown that while digital transformation can help reduce firms' pollution emissions through improved efficiency, the overall environmental impact of digitalization remains complex and multifaceted [1]. It includes five major

aspects: the energy consumption of electronic devices, the carbon footprint of data centers, water usage by data centers, the resource demands of artificial intelligence (AI)-related accelerated computing sources, and the growing issue of electronic waste (e-waste) [2].

E-waste refers to discarded electrical or electronic devices, including computers, smartphones, televisions, and other household or industrial electronic appliances that are no longer usable or have reached the end of their lifecycle. While technological solutions, including AI-based approaches, are being developed to improve e-waste management [3], in 2019, global e-waste amounted to approximately 53.6 million metric tons, with only 17.4% being properly collected and recycled. This highlights the urgent need to address the environmental consequences of digital device consumption. Moreover, e-waste has far-reaching environmental impacts that extend beyond mere accumulation. It contributes to greenhouse gas emissions, disrupts ecosystems, increases pollution, and adds to the carbon footprint—not only during usage, but also throughout production and disposal [4]. Digital pollution arises not only from physical devices, whose lifecycle, particularly during production and disposal, generates waste, but also from their usage, which demands massive data transmission and the processing of large volumes of information.

The role of AI in digital pollution is particularly complex. While AI technologies can improve sustainability by optimizing resource use, enhancing environmental monitoring, and supporting green education initiatives, they also increase the environmental footprint due to high energy consumption and emissions. For example, AI systems require substantial electricity for computation and cooling, and much of this power still comes from fossil fuels. This complexity is reflected in recent research by Zhao et al. [5], who found that while AI can effectively improve environmental quality through energy conservation and emission reduction in China, its development simultaneously creates new technological demands that may increase energy consumption. According to Oo et al. [4], the ICT sector, which includes data centers supporting AI, could account for up to 20% of global electricity consumption and a substantial portion of carbon emissions by 2030. Strubell et al. [6] found that training a single large AI model can produce carbon emissions equivalent to 284 tons of CO_2, approximately five times the lifetime emissions of an average American car. These data centers also increase water consumption and put pressure on local resources. Thus, while AI offers sustainability benefits in theory, its environmental impact is substantial and warrants careful consideration. Overall, the combination of e-waste buildup, carbon emissions from digital technologies, and their high energy consumption poses serious risks to both the environment and human health, undermining efforts to mitigate climate change.

Although awareness of general environmental issues is increasing, public understanding of the specific environmental impact of digital activities remains limited [7]. For example, while Internet use significantly contributes to digital pollution through energy consumption and data center demands, consumers often show reluctance to modify their digital habits. There is also a prevalent perception among individuals that the responsibility for addressing the environmental impact of digital technologies primarily lies with companies or governments. This perspective reveals a critical gap in perceived individual responsibility for adopting sustainable digital practices. While institutional action is indeed crucial, this reliance on external entities may lead to a lack of personal engagement in reducing digital pollution. The role of digital tools in environmental education presents a paradox. On the one hand, digital tools such as virtual reality (VR) are effective in promoting sustainability awareness and engaging learners in environmental issues [8]. On the other hand, the use of digital tools contributes to environmental problems, raising questions about how to balance educational benefits with their environmental costs. Considering the importance of digital technologies in today's educational systems, there is a pressing need for targeted environmental education that specifically addresses digital pollution.

Different countries approach the challenge of digital pollution in varied ways, reflecting their unique economic and environmental priorities. For example, in China, the interplay between digital economic growth and environmental pollution is complex; digital growth in one area may either inhibit or reduce local pollution in others [9]. National policies and economic strategies can shape the impact of digital technologies on the environment. These dynamics underscore the importance of context when addressing digital pollution and promoting sustainable practices across diverse populations. This aligns with recent research emphasizing environmental education as a fundamental preventive tool. Specifically, Cano-Ortiz et al. [10] demonstrate that environmental education serves as a crucial mechanism for preventing exposure to chemical contaminants, suggesting that similar educational approaches could effectively address digital pollution by informing citizens about the environmental impacts of their digital behaviors before such practices become entrenched and normalized.

Understanding public awareness is a crucial element in addressing the environmental impact of digital technologies. Studies demonstrate that environmental knowledge is intricately linked to pro-environmental behaviors, such as energy-saving actions in households [11]. However, psychological factors and perceived barriers also play significant roles in influencing these behaviors. For instance, Fredericks et al. [12] highlight that while tools like smart meters provide feedback on energy use, their potential to reduce digital pollution is limited by a lack of clear contextual information. Specifically, these tools fail to provide detailed breakdowns of energy consumption by specific digital devices or activities, comparisons of energy use to average household consumption or recommended levels, or clear links between energy use and its environmental impact, such as carbon emissions.

This absence of comprehensive, relatable information affects consumers' understanding of how their digital behaviors, such as device usage and online activities, contribute to energy consumption and carbon emissions, ultimately impeding effective energy-saving actions.

In recent years, awareness of digital pollution has been increasing, as evidenced by various publications and initiatives [13,14]. Websites such as EcoMatcher provide general information about digital pollution, while organizations such as ADICE (Association for the Development of Citizen and European Initiatives) offer quizzes to evaluate users' digital environmental responsibility. While these efforts are valuable for raising awareness, they often lack the depth and analytical rigor needed to fully understand and address the complexities of digital pollution literacy across diverse populations.

Our study addresses this gap by investigating how demographic factors—including age, education, income, occupation, perceived environmental knowledge, and tech-savviness—are associated with digital pollution literacy. The research question guiding this work is as follows: how do sociodemographic factors influence environmental and digital pollution literacy? We hypothesized that (1) age and tech-savviness would be positively associated with digital pollution literacy, (2) education level and income would show limited association with digital pollution literacy, and (3) environmental literacy would be positively correlated with digital pollution literacy. By clarifying these relationships, the study aims to inform educational interventions and policy measures that foster more sustainable digital practices.

Our study aims to bridge this gap by examining differences in digital pollution knowledge among various socioeconomic and demographic groups. This research seeks to identify potential knowledge gaps that require a more targeted educational approach and, ultimately, provide insights to inform educational and policy interventions. As Santarius et al. (2023) emphasized, there is an urgent need for coherent, cross-sectoral approaches to address the environmental impacts of digitalization, yet such efforts require a solid understanding of public awareness and literacy [15]. To address this need, we developed, for

the first time, to our knowledge, a comprehensive quantification tool (via questionnaires) and conducted a statistical analysis of digital pollution literacy, along with the creation of predictive models.

By providing a more nuanced understanding of digital pollution literacy across different demographic segments, our study contributes to the advancement of the digital pollution field, informing both awareness-raising initiatives and the development of tailored strategies to address this critical challenge. Additionally, the insights gained from this research can inform decision-makers, industry leaders, and other institutions in developing more effective, tailored interventions to combat digital pollution, thereby promoting sustainable digital practices across diverse populations. This aligns with recent calls for evidence-informed policies that can effectively harness digitalization's potential while mitigating its environmental risks [15].

2. Materials and Methods

2.1. Survey Design, Content, and Measures

The questionnaire used in this study aimed to assess the associations between the participants' demographic information, technological savviness, and knowledge regarding environmental issues and digital pollution. It included a series of closed-ended questions organized into specific domains to evaluate literacy on both general environmental topics and specific digital pollution issues. Table 1 describes the questionnaire structure.

Table 1. Structure of the questionnaire.

Section	Subsection/Topic	Number of Questions
(a) Demographics	Age, gender, education, income, occupation	6
(b) Self-assessment	Tech-savviness, environmental knowledge, self-efficacy	3
(c) Environmental knowledge	General knowledge on sustainability and climate change	4
(d) Digital pollution knowledge	AI and digital pollution	2
	Water usage in digital infrastructure	7
	Energy efficiency in digital devices	7
	E-waste awareness	2
	Digital pollution reduction	7
(e) Confidence	The participant's confidence in answering the knowledge questions	1
Total		39

2.1.1. Survey Development Process

The survey questions were developed based on a systematic approach. In the preliminary phase, we conducted an extensive review of academic studies and relevant resources in the fields of digital pollution, sustainability, and the environmental impact of information technologies. Key concepts were identified, and core topics and themes to be included in the survey were defined and selected. Next, varying weights were assigned to the various topics to ensure comprehensive coverage and determine the number of questions for each topic. Finally, we developed a series of questions that addressed both theoretical knowledge

and practical actions related to digital pollution and sustainability, ensuring that the survey effectively covered the key domains of digital pollution knowledge and awareness.

The environmental literacy questions were informed by prior survey instruments, including those developed by Pothitou et al. [11] and Boeve-de Pauw et al. [16], focusing on renewable energy, carbon footprint, and climate change impacts. The digital pollution literacy questions were derived from an extensive literature review [2,4,13] and expert consultations covering energy consumption of AI models, water usage by data centers, digital device energy efficiency, e-waste, and reduction strategies.

2.1.2. Scale Validity and Refinement

Content validity was ensured through alignment with these sources and expert review, while construct validity was supported by observed correlations between environmental and digital literacy scores and expected demographic associations (e.g., age and tech-savviness). To further refine the scales, a pilot survey with 50 participants was conducted. Item analysis identified and removed redundant items with high inter-item correlations ($r > 0.80$), ensuring that each item contributed unique information.

2.1.3. Questionnaire Structure and Rationale

This rigorous process ensured that our survey instrument was grounded in the current academic literature and capable of providing a comprehensive assessment of the participants' digital pollution literacy. The questionnaire was composed of four main sections:

(a) Demographics: education level, primary occupation, household income, gender, and age. This section enabled analysis of socioeconomic factors that may influence environmental awareness and provided essential variables for understanding knowledge distribution across different population segments.

(b) Technological and environmental literacy: the participants self-assessed their tech-savviness and knowledge of environmental issues and digital pollution. This section allowed comparison between the perceived and the actual knowledge, identifying potential overconfidence biases that may affect environmental behavior.

(c) Knowledge questions on environmental aspects: in this section, the questions tested the participants' knowledge on environmental aspects such as renewable energy, carbon footprint, and climate change consequences. This section established baseline environmental literacy to examine its relationship with digital pollution awareness.

(d) Knowledge questions about digital pollution: the following key concepts were addressed in this section: energy consumption of AI models, digital device usage, water footprint of data centers, and e-waste. This section directly measured understanding of the environmental impact of digital technologies.

Finally, we added a question to assess the participants' confidence in answering the knowledge questions (sections (c) and (d)), enabling analysis of the relationship between confidence and actual performance.

An "environment score" was calculated based on the number of correct answers to the general environment questions (section (c)). Similarly, a "digital pollution score" was calculated based on the number of correct answers to the digital pollution questions (section (d)). In addition, we calculated scores for each of the topics in section (d): AI, water, energy, e-waste, and digital pollution reduction (sub-group scores). These scores provided a quantitative measure of the participants' literacy on environmental and digital pollution topics, with each correct answer contributing one point to the respective score.

Sub-group scores were normalized to account for the varying numbers of questions across topics, enabling a more nuanced understanding of the participants' knowledge in specific areas of the digital environmental impact.

2.2. Participants and Data Collection

2.2.1. Sample Size Determination

Based on a power analysis, a sample size of 81 participants was required to detect a correlation of r = 0.3 with a power of 0.80 and a significance level of $\alpha = 0.05$. This would ensure that the study was adequately powered to identify meaningful associations while minimizing the risk of type I and type II errors. However, to enhance statistical power and improve generalizability, we recruited 300 participants, providing substantial statistical power for detecting smaller effect sizes and enabling robust subgroup analyses.

2.2.2. Participant Recruitment and Survey Administration

This cross-sectional survey study included 300 participants from the UK, recruited via Prolific (www.prolific.com accessed on 26 October 2024), an online platform that facilitates participant recruitment for cognitive and behavioral experiments across various research fields (2024). Prolific was selected due to its established reputation for providing high-quality data and its sophisticated sampling options that allow researchers to target specific demographic characteristics. To ensure sample diversity, specific screening criteria were applied across age groups (18–80 years), educational backgrounds, and occupational sectors. Prolific's sampling options were utilized to aim for diverse demographics, including variations in age, gender, education level, and occupation. While true population representativeness cannot be guaranteed due to online convenience sampling limitations, the platform's pre-screening features help reduce sampling bias. Moreover, we conducted our own demographic analysis to assess the diversity of our sample, as detailed in the Results section. The basic requirements for participation in the survey were a minimum age of 18 and fluency in English. The participants were recruited between 28 and 30 October 2024 and completed an online questionnaire consisting of closed-ended questions focused on demographic information, environmental knowledge, and awareness of digital pollution.

2.3. Refinements and Reliability Checks

To validate the process and the questions in the questionnaire, we first assessed the survey's primary output (digital pollution score) with two small groups of "gold standard" participants: three experts in the field of digital pollution and three non-affiliated participants. The experts achieved high scores, while the non-affiliated participants obtained low digital pollution scores, thereby confirming the validity of the questionnaire. Next, we administered a pilot questionnaire to 50 participants. Item analysis was conducted to identify potential issues with question clarity, response patterns, and inter-item relationships. Questions that had a high correlation coefficient with other questions were removed to avoid redundancy ($r > 0.80$), ensuring that each item contributed unique information to the overall assessment. In addition, to evaluate the reliability of the questionnaire, Cronbach's alpha was calculated, resulting in $\alpha = 0.753$, indicating satisfactory internal consistency according to established thresholds ($\alpha > 0.70$). The removal of any individual questions did not significantly improve reliability (change > 0.05), indicating satisfactory internal consistency, and no more questions were removed at this stage. The pilot study also confirmed that participants could complete the questionnaire within the intended timeframe and that the questions were clearly understood across different demographic groups.

2.4. Statistical Analysis

Due to the non-normal distributions of the variables, as determined by Shapiro–Wilk tests, Spearman's correlations were utilized to evaluate associations between demographic/socioeconomic variables and the participants' environmental and technological literacy scores. To explore gender differences in environmental and digital pollution (DP) scores and to compare the DP scores between pairs of occupations, we used Wilcoxon non-paired tests. Additionally, Wilcoxon paired tests assessed differences between normalized digital pollution sub-group scores. Multivariate linear regression was applied to understand associations between sex, age, environmental scores, and digital pollution scores and to capture the relationships between the multiple variables. Variables were normalized using min–max normalization, and the model's significance was evaluated using R^2, root mean square error (RMSE), and coefficients/*p*-values for each parameter. All statistical analyses were conducted using MATLAB© version R2023b. Statistical significance was set at $p < 0.05$ for all analyses.

2.5. Ethical Considerations

The study adhered to ethical guidelines, ensuring voluntary participation, informed consent, anonymity, and confidentiality. Data were collected and reported in aggregate to protect the participants' privacy. The study was approved by the institutional ethics committee (approval on 21 October 2024).

3. Results

3.1. Survey Participants

The survey sample consisted of individuals aged 18 to 80 (mean = 45.53 $\pm$ 13.16), with female participants being the majority (58.8%) compared to male participants (41.2%). In terms of educational attainment, 19.6% of the participants held a high school diploma or lower, 22.3% had completed some college, and the majority (55.5%) held a bachelor's degree or higher. Only 3% of the participants reported having a professional degree. The annual household income distribution was as follows: 3.3% reported earnings up to \$15,000, 26.6% fell within the \$15,001–\$35,000 bracket, and 34.2% indicated incomes between \$35,001 and \$70,000. The middle-to-upper income ranges were represented by 20.1% earning \$70,001–\$100,000, 7.6% in the \$100,001–\$150,000 category, and 2.7% with incomes of \$250,001 or more. Additionally, 5.5% of the respondents preferred not to disclose their income, and no participants reported no income.

The sample represented various occupations, including unemployed individuals, students, government employees, healthcare professionals, educators, and various industry professionals. The largest occupational groups were non-technology industry workers (14%), retirees (13%), and educators or teachers (9%). Table 2 provides a comprehensive summary of the demographic and background characteristics of the survey participants, including detailed breakdowns of sex, age, annual household income, and occupations.

Table 2. Demographic and background characteristics of the survey participants.

Characteristics	Categories	N	%
Sex	Male	124	41.2
	Female	177	58.8

Table 2. *Cont.*

Characteristics	Categories	N	%
Age	18–24	13	4.3
	25–34	57	18.9
	35–44	84	27.9
	45–54	57	18.9
	55–64	65	21.6
	65+	25	8.3
Annual household income	No income		
	Up to $15,000	10	3.3
	$15,001–$35,000	80	26.6
	$35,001–$70,000	103	34.2
	$70,001–$100,000	62	20.6
	$101,001–$150,000	23	7.6
	More than $150,000	8	2.7
occupations	Unemployed	15	5%
	Students	6	2%
	Government employees	21	7%
	Healthcare professionals	24	8%
	Educators or teachers	28	9%
	Artists or creative professionals	7	2%
	Marketing specialists	20	7%
	Researchers or scientists	6	2%
	Construction or other skilled tradespersons	9	3%
	Accounting professionals	15	5%
	Technology industry workers	21	7%
	Non-technology industry workers	43	14%
	Retirees	39	13%
	Other professionals	47	16%

3.2. Associations Between Socioeconomic and Demographic Variables and Self-Assessed Literacy

The study analyzed the relationships between the participants' socioeconomic and demographic variables (section (a)) and their self-assessment of environmental and technological literacy (section (b)). The key self-assessment items included (1) "How would you rate your knowledge about environmental issues?" and (2) "How would you describe your level of tech-savviness?"

A positive correlation was found between education level and self-assessed environmental literacy (Spearman r = 0.23 [95% CI = 0.12, 0.33], $p = 0.0001$, $R^2 = 5.29\%$), indicating that individuals with higher education levels are more likely to rate themselves as knowledgeable about environmental issues. While statistically significant, the practical impact is limited, as education level explains only about 5% of the variance in self-assessed environmental literacy. This limited association may reflect the subjective nature of self-

assessments, which can be influenced by overconfidence, modesty, or varying internal standards rather than objective knowledge.

Education was also positively associated with technological literacy (r = 0.24 [95% CI = 0.13, 0.34], $p < 0.0001$, $R^2 = 5.76\%$). Again, this represents a small effect size, with education accounting for less than 6% of the variance in self-assessed technological literacy, possibly due to differences in informal exposure to technology, generational trends, or the fast-evolving nature of digital tools that may not be fully addressed in traditional education. Although limited in magnitude, this association was consistent across both literacy domains, suggesting that education contributes to perceived competence. There was a negative association between age and technological literacy (r = −0.30 [95% CI = −0.40, −0.20], $p < 0.0001$, $R^2 = 9.0\%$), suggesting that younger participants tend to rate themselves as more tech-savvy. This effect size indicates a moderate relationship where age accounts for 9% of the variance in self-assessed technological literacy. This supports the observation that age-related differences in perceived tech literacy are non-trivial and practically relevant. The correlation between self-assessed environmental literacy and technological literacy was positive (r = 0.33 [95% CI = 0.23, 0.43], $p < 0.0001$, $R^2 = 10.89\%$), indicating that participants who view themselves as knowledgeable about environmental issues are likely to also consider themselves tech-savvy. This moderate effect size suggests that these self-assessments share about 11% of their variance, pointing to a meaningful, though not complete overlap between these two domains of self-perceived knowledge.

In addition, we asked the participants the following question: "How familiar are you with the concept of digital pollution?" Most participants were not familiar (30%) or were slightly familiar (43%) with this concept, 18.7% were moderately familiar, 7% were very familiar with this concept, and only 0.8% were extremely familiar with this concept. There was a statistically significant positive correlation between technological literacy and familiarity with the concept of digital pollution (r = 0.39 [95% CI = 0.28, 0.49], $p < 0.0001$, $R^2 = 15.21\%$), representing a moderate effect size where self-assessed technological literacy explains about 15% of the variance in familiarity with digital pollution concepts, highlighting a relevant link between perceived technical competence and awareness of emerging environmental issues. There was also a statistically significant positive correlation between environmental literacy and familiarity with the concept of digital pollution (r = 0.33 [95% CI = 0.22, 0.44], $p < 0.0001$, $R^2 = 10.89\%$). This means a moderate relationship between these self-assessed knowledge domains and familiarity with digital pollution. To summarize, education level, self-assessed environmental literacy, and technological literacy were all positively interrelated. Furthermore, both environmental literacy and technological literacy demonstrated positive associations with the concept of digital pollution.

3.3. Digital Pollution Scores: General and Sub-Group Scores

The survey included 25 knowledge questions regarding digital pollution (DP) (section (d)). The DP score was defined as the total number of correct answers regarding digital pollution. The lowest score was five points, and two participants answered all questions correctly and achieved the maximum score of 25 points. The median score was 19, and the mean was 18.38 ± 3.5 (See Figure 1). As for confidence, 5.1% of the participants reported they were not at all confident in their answers to the DP knowledge questions, 31.2% reported they were not very confident, 41% were moderately confident, 16.4% reported high confidence, and 2%—very high confidence. Of note, there was no correlation between the DP score and the participants' confidence in answering the DP knowledge questions (r ~ 0 [95% CI = −0.08, 0.17], $p = 0.69$, $R^2 = 0.02\%$).

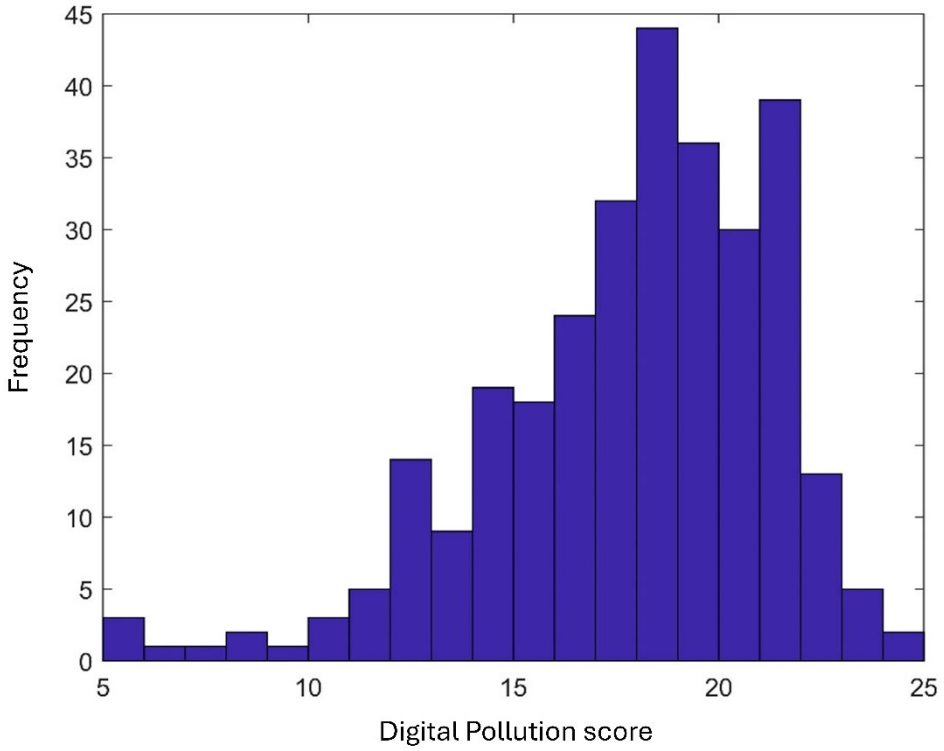


Figure 1. Distribution of digital pollution scores (N = 301).

Next, we compared the normalized sub-group scores. The digital pollution questions were divided into five groups of questions: AI, energy, water, e-waste, and reduction of digital pollution. Figure 2 shows the mean normalized scores for the different topics (sub-groups). The topic with the highest score was water (mean = 0.79 ± 0.21), while the topic with the lowest score was e-waste (mean = 0.49 ± 0.33).

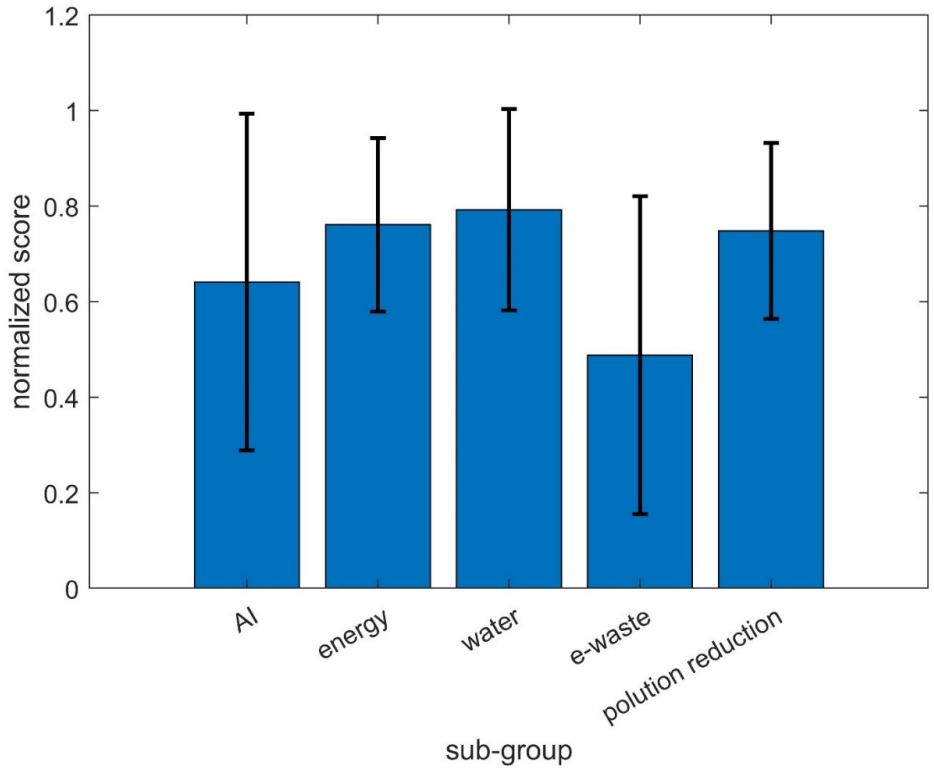


Figure 2. The mean normalized scores for the different sub-groups.

Next, we compared the normalized scores using the Wilcoxon paired test. All pairs of scores were statistically significantly different ($p < 0.0001$), i.e., the ratio of correct water-related answers was significantly higher than those regarding AI, e-waste, and pollution reduction, the ratio of correct energy-related answers was statistically significantly higher than those related to AI and e-waste, etc. The comparison of the two following pairs was not statistically significant: energy and water; energy and pollution reduction. These results indicate that there were significant differences between the participants' knowledge regarding the different digital pollution topics. Surprisingly, there was only a weak, non-statistically significant, positive correlation between the DP score and the familiarity with the concept of digital pollution (r = 0.1 [95% CI = −0.02, 0.22], $p < 0.05$, R^2 = 1%). This weak correlation suggests that familiarity with the term "digital pollution" does not necessarily reflect actual knowledge, possibly due to differences between term recognition and conceptual understanding. There was no correlation between the environment score and the familiarity with the concept of digital pollution. The lack of correlation may indicate that environmental knowledge does not inherently include awareness of digital pollution, which is a relatively new and less widely recognized aspect of environmental issues.

3.4. Associations Between Socioeconomic and Demographic Variables and Environmental/Digital Pollution Scores

We analyzed the associations between socioeconomic and demographic variables and the participants' scores, both in the general environmental literacy (environment score) and the digital pollution literacy (DP score).

While there was no statistically significant difference between men and women in their environment score, there was a statistically significant difference between men and women in their DP score: men had significantly higher scores (mean of 19.6 ± 3.1) in comparison to women (mean of 18.2 ± 3.6, $p = 0.001$).

Interestingly, there was no association between the degree of education and both the environment and DP scores. This lack of association may suggest that formal education does not directly translate into higher factual knowledge about environmental or digital pollution issues, possibly because these topics are not systematically integrated into most educational curricula.

There was also no association between household income and the two scores. The absence of association may indicate that access to financial resources does not necessarily influence individuals' factual knowledge about environmental or digital pollution, suggesting that information exposure and interest in these topics are not strongly income-dependent. Age showed a weak positive association with the DP score (r = 0.15 [95% CI = 0.04, 0.26], $p = 0.01$, R^2 = 2.25%). The participant's statement regarding his/her environmental literacy was, surprisingly, not associated with the environment score (r = 0.07 [95% CI = −0.04, 0.18], $p = 0.23$, R^2 = 0.49%), with a negligible effect size of less than 0.5%, probably since self-perceived environmental literacy is not accurate and does not represent the actual knowledge due to overconfidence or limited self-awareness. However, this environmental statement exhibited a weak positive association with the DP score (r = 0.14 [95% CI = 0.03, 0.25], $p = 0.016$, R^2 = 1.96%). As for technology literacy, it was also not associated with the environment score and showed a weak positive association with the DP score (r = 0.13 [95% CI = 0.02, 0.24], $p = 0.02$, R^2 = 1.69%). The lack of association with the environment score suggests that perceived technological competence does not imply greater environmental knowledge, while the weak positive link with the DP score may reflect a limited but meaningful connection between tech-savviness and awareness of digital environmental issues. Of note, the two scores (environmental and technological) were positively associated (r = 0.26 [95% CI = 0.15, 0.36], $p < 0.0001$, R^2 = 6.76%). This represents a small to moderate effect size, suggesting that environmental and technological knowledge share about 6.76%

of their variance. While this is the largest effect size observed in these relationships, it still indicates a relatively modest practical relationship between these two knowledge domains (see Table 3). In summary, digital pollution literacy (DP) scores were higher among men. The score was positively associated with age, self-assessed environmental literacy, and technological literacy, while environmental and technological literacy were also positively correlated.

Table 3. Spearman correlations between self-assessment of the participants' environmental and technology knowledge and the participants' environmental and digital pollution knowledge based on the study's questionnaire.

	Questionnaire-Based Environmental Knowledge		**Questionnaire-Based Digital Pollution Knowledge**	
	R	*p*	r	*p*
Self-assessed environmental knowledge	0.07	0.23	0.14	0.016
Self-assessed tech-savviness	−0.1	0.1	0.13	0.02

Next, we compared DP scores between different occupations. The occupations with the highest DP scores were researchers and scientists, with a mean score of 22.3 ± 0.82, and employees in the technology industry, with a mean score of 20.4 ±2.5. The occupation with the lowest DP scores was students, with a mean score of 15.2 ± 4.8 (Figure 3). Comparison of the DP scores between the groups showed that researchers and scientists had statistically higher DP scores in comparison to all other occupations, excluding artists/creative professionals, and that employees in the technology industry had statistically higher DP scores in comparison to all other occupations, excluding government employees, artists/creative professionals, construction and other skilled tradespersons, and non-technology industry employees.

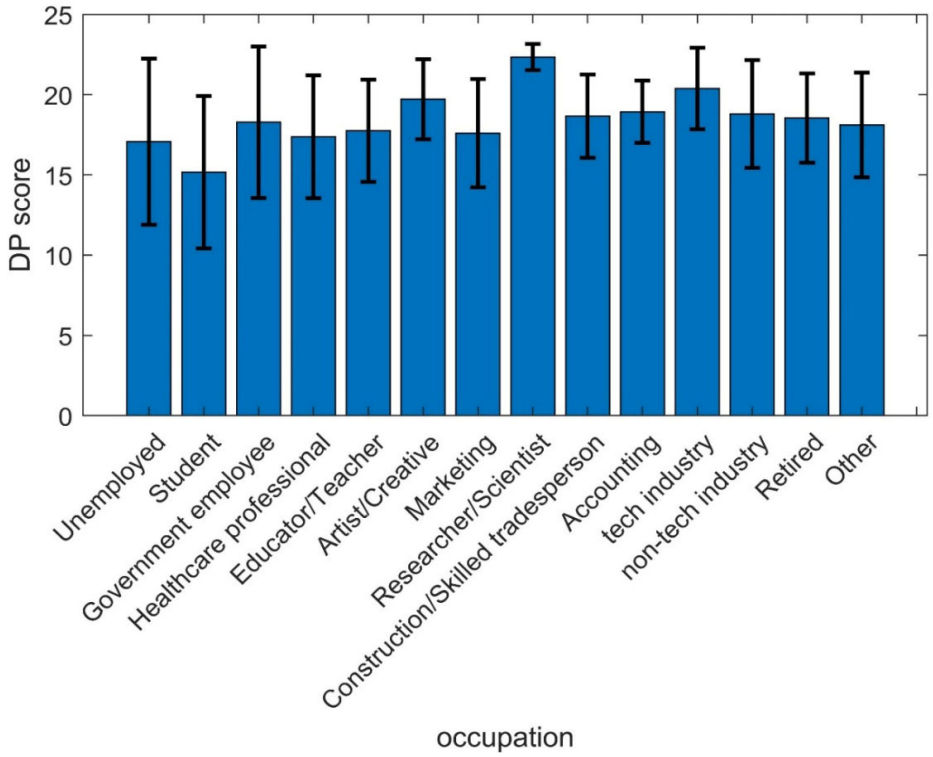


Figure 3. Comparison of DP scores according to the participants' occupations.

3.5. Models for the Prediction of the Digital Pollution Score

To explore the complex relationships between variables, a multivariate linear regression model was used to predict digital pollution scores, employing sex, age, and environment score as the predictors. The model was statistically significant ($p < 0.0001$, $R^2 = 0.14$ [95% CI = 0.07, 0.24], RMSE = 3.24 [95% CI = 2.91, 3.56]). The results indicate that the model explained 14% of the variance in digital pollution scores.

All variables statistically significantly contributed positively to the model, with the environment score being the most influential predictor (β = 3.93 [95% CI = 3.92, 3.94], $p < 0.0001$) (see Table 4).

Table 4. Linear regression model for the prediction of digital pollution scores.

Variable	β	β 95% Confidence Intervals	*p*
Intercept	13.85	[13.84, 13.86]	<0.0001
Sex	1.35	[1.34 1.35]	0.0004
Age	2.26	[2.24 2.27]	0.011
Environment score	3.93	[3.92 3.94]	<0.0001

Of note, incorporating either the technological statement or the environmental statement into the model did not change its performance.

4. Discussion and Future Directions

4.1. Discussion

This study provides valuable insights into the relationships between sociodemographic factors, environmental knowledge, and digital pollution literacy. Our findings reveal a complex interplay of variables that influence knowledge and awareness of digital pollution issues, carrying significant implications for education and policy.

Our primary finding is that most of the participants (73%) were not familiar or were only slightly familiar with the concept of digital pollution. Furthermore, although the participants tended to answer the questions regarding digital pollution correctly, their overall confidence regarding their answers was low. Only 18.4% of the participants stated they a had high or very high confidence in their answers to the DP knowledge questions.

Contrary to expectations, neither education level nor income showed significant associations with digital pollution literacy or general environmental knowledge. The effect sizes for these relationships were negligible ($R^2 < 1\%$), underscoring the lack of practical significance in the associations between education or income and environmental knowledge or digital pollution literacy. This surprising finding challenges the assumption that higher education or income automatically leads to better environmental awareness. This finding aligns with Meyer's study [17], which found that the relationship between education and pro-environmental behavior is complex and not always straightforward due to potential confounding factors. Meyer noted that individuals who attain more education may differ in unobservable ways that also influence their environmental attitudes and behaviors. For example, personal characteristics, such as social conscience or work ethic, could affect both educational attainment and pro-environmental tendencies. Without being able to control for all such factors, the true causal relationship between education and environmental behavior is difficult to establish through standard correlational analysis. Additionally, it is possible that the current educational curricula may not adequately address digital pollution and environmental sustainability at all levels. There is a clear need to integrate these topics more comprehensively into educational frameworks, regardless of academic level or socioeconomic status, as also emphasized by Boeve-de Pauw et al. [16].

Educational institutions should implement national and institutional policies that include digital sustainability topics, supported by targeted materials and teacher training.

Supporting this recommendation, Wang and Si [18] emphasized the importance of public libraries as inclusive spaces for advancing digital literacy and social equity. Their study highlighted how effective public policy, particularly when aligned with educational initiatives, can leverage community infrastructures to promote digital inclusion and support sustainable development goals.

This finding resonates with the structural analysis by Tian and Chen [19], who examined the environmental literacy of urban residents in Qingdao, China. They concluded that demographic factors alone—such as education or income—do not strongly predict environmental behavior, emphasizing the importance of contextual and cognitive factors over structural demographics.

This pattern appears across different educational domains. For instance, Ceylan et al. [20] found that among dental students, demographic factors such as age, grade level, and residence type did not significantly influence perceptions of professional competence, further supporting the observation that traditional demographic predictors may be less relevant for understanding competency perceptions in contemporary educational contexts.

These cross-disciplinary findings suggest that educational interventions should focus on content-specific factors rather than demographic targeting.

The results show a weak positive correlation between age and digital pollution scores ($r = 0.15$, $p = 0.01$), with older participants demonstrating slightly better knowledge of digital pollution. However, the effect size of this relationship is small ($R^2 = 2.25\%$), indicating that age explains only a minimal portion of the variance in digital pollution knowledge. This limited effect size highlights the need for cautious interpretation and emphasizes the importance of practical, age-appropriate interventions to improve digital sustainability literacy. This finding is particularly interesting when compared with self-assessed tech-savviness, where younger participants rated themselves higher. This partial inconsistency highlights a potential overconfidence among younger individuals regarding their understanding of technology's environmental impact. As observed in similar studies on public perception of technological risk, such as those examining AI perceptions [21], there often exists a disconnect between self-perceived competence and evidence-based literacy, a pattern that is reflected in our findings. A similar trend was reported by Li et al. [22], who found that although rural youth in China demonstrated high levels of digital literacy, this did not translate into environmentally sustainable behavior—further supporting the notion that digital fluency does not necessarily imply ecological awareness.

Such misalignment between perceived and actual knowledge is a well-documented phenomenon in cognitive psychology, termed the Dunning–Kruger effect [23].

Theoretically, this suggests cognitive biases should be addressed in educational strategies, while practically, it highlights the need for clear, actionable learning materials that directly address these misperceptions.

Our findings suggest a need for targeted digital literacy programs that specifically address the environmental consequences of technology use, especially for younger demographics who may be frequent users but less aware of the ecological footprint of their digital activities. It is, therefore, advisable to develop age-appropriate educational materials and programs that address the specific knowledge gaps that were identified in the current study among different age groups, focusing on practical, actionable information that can lead to behavior change. Theoretically, this suggests cognitive biases should be considered in designing educational strategies, while practically, it underscores the need for clear, actionable learning materials that directly address these misperceptions.

This recommendation echoes conclusions from a recent systematic literature review by Fernández-Otoya et al. [24], which found that digital and information literacy programs for teachers are often fragmented and lack comprehensive integration. Their analysis highlighted the importance of embedding sustainability-related content into digital literacy training, particularly for educators, who serve as multipliers of knowledge and values.

A positive association was observed between environmental literacy and digital pollution literacy (r = 0.26, $p < 0.0001$), suggesting that individuals with a solid foundation in general environmental issues are more likely to understand digital pollution concepts. The effect size of this relationship ($R^2 = 6.76\%$) suggests a moderate practical significance, indicating that while there is some overlap between these knowledge domains, they largely remain distinct areas of competence. This highlights an opportunity to integrate digital pollution topics into broader environmental education programs while recognizing the distinct challenges of digital sustainability. The results also revealed a notable discrepancy between self-assessed and actual literacy. The participants' self-reported environmental literacy was not associated with their actual environmental scores, but showed a weak positive association with digital pollution scores (r = 0.14, $p = 0.016$). Similarly, self-assessed technological literacy was also weakly associated with digital pollution scores (r = 0.13, $p = 0.02$). Furthermore, there was a contradiction between the participants' statement regarding their familiarity with DP concepts and their actual DP score, as shown by the weak correlation between these two measurements, again referring to the Dunning–Kruger effect [23]. This gap between perceived and actual literacy aligns with findings from related domains. For example, a study of air pollution health literacy among active commuters in Hamilton [25] found that individuals who frequently engaged in environmentally positive behaviors—such as choosing active transportation modes—tended to overestimate their actual understanding of pollution-related health risks. The study revealed that despite their environmental engagement, most participants exhibited low self-rated knowledge and failed to adopt protective behaviors against air pollution exposure. This suggests that habitual or confident engagement with "green" practices does not necessarily reflect accurate or comprehensive knowledge patterns, a pattern that resonates with the digital realm as well. The analysis of the normalized scores of the different digital pollution subtopics revealed significant variations in the knowledge demonstrated by the participants. The highest literacy score was found in water-related issues (mean = 0.79 ± 0.21), and the lowest score was found in e-waste (mean = 0.49 ± 0.33).

The comparison of digital pollution (DP) scores between occupations revealed that researchers/scientists and technology industry employees had the highest scores, while students had the lowest. However, these findings should be interpreted with extreme caution due to the relatively small sample sizes in some categories, particularly researchers/scientists (n = 6). While these results hint at potential associations between occupation and digital pollution awareness, further research with larger, more representative samples is necessary if any meaningful conclusions are to be drawn.

4.2. Policy and Educational Implications

From a policy perspective, these findings underscore a pressing need for comprehensive environmental education policies that explicitly include digital pollution and sustainability. A systemic approach is needed to integrate these topics into school curricula, university programs, and teacher training, supported by targeted materials and professional development. These findings align with earlier calls to integrate broader conceptions of scientific literacy into curricula, not only to foster conceptual understanding, but also to promote affective engagement and civic responsibility in sustainability issues [26]. Following the framework proposed by Cano-Ortiz et al. [10], who advocate for environmental

education as a fundamental tool for preventing chemical contamination exposure, we recommend implementing digital pollution education as a preventive strategy. Such an approach can equip citizens with the knowledge and critical awareness needed to make informed decisions about sustainable digital practices.

4.3. Study Limitations

While this study provides valuable insights into the relationships between demographic factors and digital pollution literacy, several limitations should be considered when interpreting the results. Although the sample of 300 participants was relatively large and diverse, it may not be sufficient to represent the UK population. The online survey format restricted participation to individuals with Internet access and digital literacy, potentially skewing the results toward a more digitally literate population and overestimating general digital pollution awareness. Since this study utilized a questionnaire rather than an in-depth interview, it is possible that the participants may have guessed some answers or provided responses based on what seemed most appropriate to them, without necessarily possessing a deep understanding or knowledge of the subject matter. Additionally, reliance on self-reported data introduces the potential for biases, such as social desirability bias, where participants may overstate their knowledge or environmentally friendly behaviors. This may result in discrepancies between the perceived and actual knowledge or behaviors. Additionally, the unequal number of questions across digital pollution topics, some with seven questions and others with only two, may affect the reliability and comparability of sub-topic scores, potentially impacting the overall assessment of digital pollution literacy. Similarities in the content of certain questions may have also provided clues, potentially inflating scores for related topics and influencing the accuracy of sub-topic assessments. The cross-sectional design of this study provides only a snapshot of digital pollution literacy, at one point in time, limiting the ability to draw causal inferences or observe changes in knowledge and attitudes over time. Moreover, the focus on the UK population may limit the generalizability of findings to other cultural or geographic contexts, as awareness and attitudes toward digital pollution can vary internationally. Finally, the participants who opted to complete the survey may have had a pre-existing interest in environmental issues, potentially leading to a sample with higher-than-average environmental awareness. These limitations highlight the need for future research using longitudinal designs, qualitative methods, and larger, more diverse samples to confirm and extend these findings.

4.4. Future Research Directions

The findings of this study open multiple avenues for future research aimed at deepening our understanding of digital pollution literacy and its social, educational, and behavioral implications. Given the novelty and complexity of the digital pollution concept, further research is needed to explore the structural, psychological, and cultural factors that shape both awareness and knowledge in this domain. First, cross-country comparisons should be conducted to examine how digital pollution literacy varies across countries with different educational systems, environmental policies, and cultural attitudes toward technology. Such studies could help identify global disparities and develop region-specific educational strategies. Second, longitudinal research is recommended to assess how digital pollution knowledge and behaviors evolve over time, particularly in response to interventions such as curriculum changes, public campaigns, or shifts in digital consumption patterns. Tracking changes over time would provide valuable insight into the effectiveness of awareness-raising efforts and the sustainability of behavior change. Third, qualitative approaches, including interviews, focus groups, and ethnographic methods, could offer rich, contextualized insights into how individuals understand and emotionally respond

to digital pollution. These methods may help uncover barriers to action and reveal the role of personal values, trust, and media framing in shaping public attitudes. Fourth, evaluations of educational approaches, such as workshops, online courses, or gamified learning experiences, would offer actionable evidence for educators and policymakers to design more effective interventions. Fifth, future research should seek to develop and validate comprehensive tools for measuring digital pollution literacy, distinguishing between factual knowledge, perceived familiarity, and behavioral intention. Such tools would allow for more nuanced analysis at both individual and group levels. Finally, collaboration among educators, environmental experts, and technology developers will be critical for fostering innovative solutions that address both educational and environmental challenges, ultimately promoting a more environmentally conscious digital society.

5. Conclusions

This study explored the relationships between demographic factors, environmental knowledge, and digital pollution literacy among UK participants. Our findings challenge assumptions about the influence of education and income on digital pollution literacy and highlight gaps between the perceived and actual knowledge. These insights emphasize the need for targeted educational strategies that integrate digital pollution awareness into broader environmental education.

Notably, we found a positive correlation between general environmental literacy and digital pollution literacy, yet this finding is not consistent across all demographic groups. This study presents the first comprehensive quantification tool for assessing digital pollution literacy, addressing a significant gap in environmental education research. Unexpectedly, education level did not significantly impact digital pollution literacy, suggesting there may be a gap in the current environmental education curricula. This finding is particularly novel, especially as it challenges the assumption that higher education automatically leads to a better understanding of emerging environmental issues, such as digital pollution.

Another interesting result was the relationship between age and digital pollution knowledge. While younger participants rated themselves as more tech-savvy, they demonstrated less comprehensive knowledge of digital pollution compared to older participants. This discrepancy between self-perceived technological literacy and actual understanding of its environmental impact is a key contribution of our study. This finding challenges the common assumption that younger generations, often referred to as "digital natives," inherently possess a more comprehensive understanding of digital technologies and their implications [27]. Our results suggest that while younger individuals may be more comfortable with using digital technologies, this familiarity does not necessarily correlate with awareness of the environmental consequences of digital activities.

Practically, the findings suggest that educational institutions should develop and implement curricula that address digital pollution at multiple levels, from primary to higher education. Theoretical implications include understanding the cognitive biases underlying misperceptions of digital sustainability and the need to link environmental literacy to digital behaviors. The development of tailored teaching materials—such as case studies, interactive modules, and simulations—can enhance digital pollution literacy and empower students to adopt sustainable digital practices. By equipping future generations with both knowledge and critical awareness, these interventions can contribute to reducing the environmental impact of digital technologies and promoting sustainable digital citizenship.

In conclusion, as digital technologies increasingly become more integrated into daily life, it is crucial to understand the interplay between demographic factors and digital pollution awareness. This study's findings offer a nuanced perspective on these associations and highlight the need for more targeted educational strategies that promote sustainable

digital behavior. By addressing the identified knowledge gaps revealed in the current study in digital pollution awareness, and more particularly those related to energy consumption, e-waste, and the environmental impact of everyday digital activities, and by tightening the relationships between environmental and digital literacy, we can work towards a more environmentally conscious digital society. This study's findings offer a nuanced perspective on these associations and highlight the need for more targeted educational strategies that promote sustainable digital behavior. However, these conclusions should be interpreted with caution, given the limitations of the study, including its cross-sectional design, limited sample from the UK, and reliance on self-reported data. Future research with larger, more diverse populations and longitudinal methods is needed to confirm and expand upon these findings.

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