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Environmental footprint of GenAI – Changing technological future or planet climate?

Vaclav Moravec [a], Beata Gavurova [b,*], Viliam Kovac [c]

[a] Institute of Formal and Applied Linguistics, Faculty of Mathematics and Physics, Charles University in Prague, Czechia
[b] Center for Applied Economic Research, Faculty of Management and Economics, Tomas Bata University in Zlin, Czechia
[c] Technical University of Košice, Košice, Slovakia

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ABSTRACT

The beginnings of generative artificial intelligence (GenAI), led by Chat Generative Pre-Trained Transformer (ChatGPT), not only change the behaviour of digital media ecosystem users but also increase the energy consumption of enterprises working with GenAI, which presents them with a fundamental challenge in the era of climate change. This study aims to examine the relationships between the selected aspects of the use of GenAI tools and the environmental perception and behaviour of their users to understand the population's current environmental attitudes towards environmental risks and environmental sustainability. The survey was conducted in October 2024 on a sample of 1,268 respondents of the Czech Republic population. To process the data set, a logistic regression analysis, chi-squared test, Akaike information criterion, and Bayesian information criterion are employed. The results show that the more often people use GenAI tools, the more distant they consider the effects of climate change in time. The low frequency of use of ChatGPT may influence a higher willingness to change popular GenAI tools that are not maintained by environmentally friendly data centres. The frequency of ChatGPT use influences individuals' perception of the importance of climate-change solving. The more frequently the respondents use artificial intelligence (AI) systems, they less perceive climate change as important. The low frequency of ChatGPT usage is associated with lower willingness to change email provider, transfer own data, leave social networks, stop using a favourite streaming platform and stop using a favourite GenAI platform. The respondents' attitudes show a visible behavioural change. Internal personal motivation and self-confidence in learning, interest in career and self-confidence when using AI, the behavioural aspects, and the cognitive aspects are altered considerably. Based on the outcomes of the population survey, the study concludes that the issue of environmental friendliness of AI tools should become part of AI literacy that could strengthen population's willingness to use more energy-efficient GenAI platforms. The listed challenges are important in the perspective of the latest technological development, as shown by the discussion on the energy and computational demands of the GenAI platform DeepSeek, which is also discussed in the study.

Introduction

Artificial intelligence (AI), as a high technology, can transform not only many industries but also the way society functions. According to estimation, global spending on AI technologies across all industries in 2023 was 154 billion USD. Within all the observed industries, the majority of spending was in the banking sector – 20.6 billion USD (Alzoubi and Mishra, 2024). Many AI technologies can significantly reduce greenhouse gas emissions in almost all industrial sectors. However, without sustainable energy sources and adequate ethical supervision, AI can seriously harm the environment and disadvantaged populations (Kelly, 2022). Vinuesa et al. (2020) examined that out of the 169 United Nations Sustainable development goals, AI can positively impact up to 134 goals and negatively impact 59 goals. The AI systems, which are powered by non-renewable resources, can significantly reduce the environmental benefits of AI.

Higher AI performance is also associated with higher energy consumption, while a large amount of global energy consumption comes from non-renewable sources such as coal and natural gas. Energy consumption for AI has a considerable carbon footprint (Chen et al., 2024a). According to some experts, GPT-3, with 175 billion parameters, consumes up to 1287 MWh of electricity and produces 552 tons of CO_2

* Corresponding author.
E-mail addresses: vaclav.moravec@ufal.mff.cuni.cz (V. Moravec), gavurova@utb.cz (B. Gavurova), viliam.kovac@tuke.sk (V. Kovac).

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equivalent – the same amount produced by 123 gasoline-powered passenger cars per year. Determining the exact energy consumption of a single generative AI model, which includes the energy required to manufacture the computational hardware, develop and run the model, is difficult; thus, estimation is applied. This is also due to the potential fluctuation of parameter values owing to the rapid development of GenAI models.

According to Xing and Monck (2023), new AI servers will have high energy demand, which raises concerns about environmental sustainability. Experts have argued that the power and functionality of AI will grow along with energy requirements, leading to the emergence of data server farms where reliable energy is available (Johnraja et al., 2024). AI's energy demand is considered incompatible with zero emissions, as highlighted by many critics and activists promoting saving the planet and the whole population. Despite the wide scientific consensus on the impact of climate change, many people do not perceive these processes as a global threat that affects the population's different attitudes towards climate change.

In many countries, efforts are made to mitigate the impact of climate change and create a space for the environmental strategies adoption (Akanwa et al., 2019; Fawzy et al., 2020). This has also stimulated the development of the so-called green AI concepts that emphasise energy consumption, reduction of CO_2 emissions from the use and training of AI models, and environmental sustainability. A wider AI ecosystem is being gradually constructed, which includes a large network of enterprises, organisations and individuals supporting the development, implementation and use of AI tools aimed at supporting and achieving sustainability (Prokop et al., 2024). The number of these green AI initiatives has been constantly growing (Bald, 2023), but their comprehensive classification is missing. Some authors have shown that green AI initiatives dominate fields such as efficient energy management and sustainable production (Wu et al., 2022; Verdecchia et al., 2023) or explored the wider implications of AI technologies for their sustainability. Some have investigated the technical aspects aimed at increasing the environmental efficiency of AI technologies; others have investigated hardware and software elements and the structure of deep learning (Lee & Kwon, 2017; Sellami and Tabbone, 2022) and deep-learning training (Tu et al., 2023), among others. Bouza et al. (2023) indicated that tools exist for monitoring energy consumption during model training and for optimising resource use to diminish their negative impact on the environment. Optimisation models also require costs quantification, which is appropriate to apply methodologies and algorithms for social and environmental sustainability (Chen et al., 2024b).

Measuring the total energy consumption of AI model production is especially difficult because the enterprises producing these models do not track these parameters. Nevertheless, studies quantifying the environmental impacts of AI have emerged (Vinuesa et al., 2020). Wu et al. (2022) examined the carbon footprint across the whole life cycle of model development, hardware lifetime, operational procedures and manufacturing phases. To reduce the total carbon footprint, the device's whole life cycle must be examined, and energy-efficient practices must be used in deep-learning training (Mehlin et al., 2023). Supporting green AI initiatives is required for a greener and more sustainable future and technological development. Some authors have considered introducing energy consumption as a success metric in deep learning for the purpose of green AI (Bae & Ha, 2021). Rohde et al. presented an evaluation framework with the 19 sustainability criteria for sustainable AI. At the same time, growing evidence indicates that green AI initiatives have been making substantial progress and creating new opportunities for enterprises developing AI models (Amankwah-Amoah et al., 2024; Feuerriegel et al., 2024; Sedkaoui & Benaichouba, 2024). This is gradually creating a relationship between AI enterprises and sustainability, as well as social responsibility, which is has not been adequately addressed within the framework of AI development.

These consistent facts declare a strong interest of both the government and technological sphere for a deeper investigation of the environmental impact and impact of GenAI and at the same time, defining the clear role of actors in the digital ecosystem. The human – user of GenAI – finds themselves in a critical and visible position, generating increasing demand for green AI; thus, they can directly influence the environmental sustainability of AI development. In other sectors, environmental thinking and consumer behaviour have become a common phenomenon with so-called standard support tools and policies; conversely, in the field of information technology and innovative technologies, this depends on many cognitive and psychosocial aspects. It is also influenced by the attitudes and experiences of users with AI technologies in both work and private life. The investigation of these aspects defines a substantial research gap that this study attempts to fill, and the conceptual side and multidimensional levels of investigation of behavioural aspects in relation to GenAI tools represent the study's originality. No research studies have been conducted with this definitional framework and in this process structure so far, which provides a space for subsequent research and the potential for targeted policy development.

Theoretical background

GenAI using large language models has a strong and deep impact on every field of society, which distinguishes it from traditional communication systems such as interpersonal communication or mass media. According to Chen et al. (2024a), GenAI strengthens or weakens the position of the various social groups and raises the question of ensuring fair benefits for all the members of society. Concerns about the effects of GenAI on people and society are diverse and have been constantly growing. For instance, concerns have begun to arise about the loss of the critical thinking skills needed to recognise errors or bias in AI responses, as well as the fact that computers will gradually be considered more unbiased than human, leading people to unconditionally accept information generated by AI. Some concerns have also emerged about the population's strong dependence on AI, which people will lose the ability or motivation to think independently, as well as concerns that inconvenient information will be considered false, or concerns about the decline in the whole society's intelligence level. For instance, accepting answers prepared in advance can reduce the population's motivation to force the programme to search for the right answers.

Cave and Dihal (2019) classified the elementary fears and hope of using AI into four categories, each containing a hope and parallel fear related to control: the hope of living much longer and the fear of losing identity, the hope of living without work and the fear of being redundant, the hope of fulfilling all the human desires with the help of AI and the fear of human redundancy, the hope of AI power over others and the fear that AI will turn against humans. AI remains highly ambiguous, both in political and cultural contexts. Without defining the ethical and technological boundaries of AI, managing and interacting with AI systems will be particularly difficult (Stahl et al., 2022).

The wider societal impacts of AI have begun to be perceived critically by many people as they are related to wider economic and social issues (Mikalef et al., 2022). Many people also have exaggerated expectations from the use of AI and its strong impact on the various aspects of life – especially regarding employment and energy consumption (Dwivedi et al., 2021). Nonetheless, they are exposed to information asymmetry and missing information. The strong potential of AI has also defined endangered professions, such as doctors, lawyers, journalists, psychologists, artists, and service providers, meaning a strong intervention in labour market policy and the restructuring of human resources.

Use of genai in relation to climate change perception

Technological development also brings new perspectives on environmental policy, which is evident from the development of opposing attitudes towards technologies and their impacts (Leipold et al., 2019;

Alkaf et al., 2023). Various emerging activist groups promote negative perceptions of AI, criticise mainstream climate programs and provoke resistance and antireflective tendencies towards environmental policies and issues. Some extreme views present climate change as a scam (Lewandowsky, 2021). Several studies have warned of the risks of organised contrarianism, which enables the targeted spread of disinformation about climate change (Coan et al., 2021; Almiron et al., 2023). This can cause confusion in public perception, deepen political polarisation and weaken efforts to adapt tools to mitigate the impacts of climate change.

The spread of climate change disinformation can also be created and financed by a network of actors, politicians, media, sponsors – industry and energy sectors – and contrarian online bloggers (Treen et al., 2020). The absence of regulation, as well as the high level of anonymity of social platforms, creates the conditions for the spread of anti-mainstream content about climate change (Vasiljev, 2024). The lack of enforceable regulation of AI on a global scale may worsen racist and nationalist prejudices, leading to countless economic, social and environmental damage (Vinuesa et al., 2020). Pearce et al. (2019) recommended studying blogs to understand climate change disinformation that spreads quickly and effectively through social networking platforms and thus filter and eliminate forms of climate disinformation dissemination. Nowadays, an interdisciplinary approach and collaboration of many stakeholders are rudimentary to develop effective solutions to eliminate harmful online disinformation processes (Saura et al., 2023).

The development, deployment and use of AI can be perceived differently by the population and how this perception can be altered over time and under the influence of various socio-economic factors remain unclear. A completely elementary view of the perception of AI is its association with strong optimism or deep pessimism, as presented by Cave and Dihal (2019). This extreme also explains the visible gap between common AI narratives and the expected impacts of AI on society (Hudson et al., 2023), as well as the need for the population's environmental literacy.

Recently, the role of GenAI in engaging with social issues such as climate change, racial justice, geopolitical issues, and health inequality, has been increasingly explored (Chatterjee, 2024). Few studies have examined how GenAI can help address these topics across diverse user groups. Chen et al. (2024b) reflected on this fact and applied an extensive audit of algorithms to evaluate dialogues between the third version of ChatGPT and participants with different perspectives on climate and racial justice issues as well as with different user experiences and conversational styles based on socio-demographic factors. The outcomes showed that users with less education were less likely to engage in AI conversations, while more educated respondents showed significant changes in the attitudes towards climate change. Thus, if AI is designed to be inclusive in relation to the different educational and other socio-economic parameters, it can be an effective tool to change public perspectives and attitudes and can also have strong educational potential (Galaz et al., 2021).

The preferences and perceptions of AI aspects vary among users. Ioku et al. examined the preference parameters for selecting AI assistants such as transparency, environmental sustainability, and performance. Respondents preferred transparency over performance but performance over environmental sustainability. Future-oriented consumers placed greater emphasis on environmental sustainability than present-oriented consumers. Sarathchandra and Haltinner (2021) explored the perceptions of the population that is sceptical of climate change and believes that it is a hoax. They confirmed the influence of socio-demographic and socio-political factors on climate scepticism. Sceptics were more likely to be male, politically conservative, older, more religiously oriented, better educated and with higher income levels.

Some studies have also pointed to the importance of investigating the implications of GenAI on electronic waste and its management strategies. According to Wang et al. (2024), implementing circular economy strategies along the green AI value chain could reduce electronic waste generation by 16 % to 86 %, increasing the importance of proactive electronic waste management regarding green AI technologies.

Alzoubi and Mishra (2024) summarised the green AI initiatives to date into six main areas: cloud-based optimisation tools, model efficiency tools, carbon footprint tools, sustainability tools, open-source initiatives and green AI communities. Kirkpatrick et al. (2024) confirmed that government organisations are already beginning to recognise the importance of green AI, even though specific regulations are not yet in place. The European Union has also taken a proactive stance towards AI policies. From the perspective of the mandate of international organisations such as the United Nations and Organisation for Economic Co-operation and Development, clear efforts are being made to create global standards for AI governance.

Some authors have pointed to the need to quantify and take into account the social and environmental impacts of GenAI – such as energy and resource consumption, working conditions and differences in accessibility – and criticise their insufficient consideration in development and deployment (Hosseini et al., 2024). Not all social and environmental impacts are clear and quantifiable; who should manage the calculation and mitigation of these impacts and what tools and mechanisms are appropriate to use remains unclear.

Environmental impact of data centres and their influence on changing behaviour of GenAI users

In relation with the digital transformation of the global economy, data generation and processing using cloud computing, big data analytics and online services, which are essential for many financial and business operations, have been increasing (Edwards et al., 2024). Energy-intensive applications also put strong pressure on data centres and the expansion of their capacities. The data centres all over the world are >6000, and their annual growth in the future is expected to be 15 %. One-third-of them are localised in the United States (Brocklehurst, 2021; Hogan, 2023). Recently, research studies have promoted the importance of data centres within digital infrastructures (Johnson, 2019; Ortar et al., 2022) and presented this as an interdisciplinary research field (Ávila-Robinson & Sengoku, 2017; Nowakowski et al., 2019; Saura et al., 2022). The rapid expansion of data centres is also associated with an increase in energy consumption. While an estimated share of 2.1 % to 3.9 % of global carbon emissions is contributed by information communication technologies, data centres account for an estimated share of 45 % (Dobbe & Whittaker, 2019; Freitag et al., 2021).

AI tools associated with deep learning and generative models require huge computing resources associated with energy-intensive hardware, graphics processors and tensor processing units, which consume much more energy than traditional processors (Ermakov, 2024). The growing needs of AI data centres can be risky in relation to the existence of energy demands of other sectors and various electrified industries. According to Dhar et al. (2022), the emissions produced by a data centre can vary by up to 40 times depending on the local network's energy sources. Hence, countries must create energy strategies that ensure investments in the modernisation of energy infrastructure and networks and thus also integrate renewable energy, so that energy is not only reliable but also affordable.

Data centres will be more deeply integrated into everyday life and will need to adapt quickly to manage the rising volume of information. Training AI models – especially deep-learning and generative models – requires processing large data sets over long time periods and with continuous calculations on thousands of high-performance graphics processing units and tensor processing units. The computational and energy demands of AI will grow exponentially, making AI technologies one of the most energy-intensive technologies. AI is now part of the most important sectors, such as healthcare, finance, defence and services. Analytical reports confirmed that since the year 2020, global demand for electricity in data centres has grown at an average annual rate of 20 % and exceeded 400 TWh by 2023. Currently, energy consumption in data centres represents approximately 1.6 % of global electricity consumption. According to the latest projections (Data Age, 2025), global data volumes could reach 335 ZB by the year 2030 – up from 64 ZB in the year 2020. Some scenarios for data centres and AI predict a substantial increase in electricity demand from 414 TWh in 2023 to 770 TWh to 1560 TWh by 2030 (Ermakov, 2024), with the most realistic scenario predicting a 174 % increase to 1135 TWh by 2030. This increase represents a critical challenge for energy systems. Hence, ensuring the continuous operation of data centres and meeting their growing energy needs will be necessary. Anderson (2024) reports global energy consumption of data centres in 2022 at approximately 460 TWh and expects it to double to >1000 TWh by 2026, which is, for instance, approximately equal to the total electricity consumption of Japan.

The latest results published in the Gas Outlook 2050 (Naderian et al., 2024) highlighted an increase in energy demand from data centres and AI and, at the same time, an increase in uncertainties related to the problematic estimation of the extent of their growth. So far, no analyses have been conducted on this issue, but various scenarios have been developed based on the forecasts of the development of data centres and AI by 2030. Many factors influencing the progress of data centres might not have yet been identified. They arise simultaneously with technological development and increasing global pressure for the intelligence of households, cities and industries. A steep increase in data generation is also expected, requiring considerable computing power. This fact raises concerns that subscribers will have to pay higher electricity rates to accommodate the development of AI, regardless of whether they obtain direct benefits. Big data, machine learning model developments and AI will play an important role in the energy market in the future (Ahmad et al., 2021).

Position of AI literacy in the concept of green artificial intelligence

Arif and Changxiao (2022) confirmed that AI literacy and subjective AI norms can positively influence the population's attitudes towards GenAI technologies and their intention to use GenAI. According to many experts, the environmental dimensions belong among the ethical dimensions. Environmental ethicists highlight the non-environmental dimensions of AI, such as its environmental footprint, as part of the ethical dimensions of AI and consider them an important factor in AI adoption.

Frank et al. (2021) explored the differences between technologies, consumers and countries in generating demand for AI products but did not rely on environmental considerations to examine the effects of utility on demand for AI products. Yigitcanlar et al. (2024) examined the drivers of public perception of AI, confirming that perceptions of AI may vary by local context. The most important factors influencing public perception of AI include sex, age and AI knowledge and experience. Although AI literacy contributes to building trust and minimising public concerns about AI, the impact extent on trust and adoption of AI may differ across geographical and socio-economic contexts.

Galaz et al. (2021) warned about the systemic risks of AI sustainability owing to the quick spread of the AI technologies into new social, economic and ecological contexts and thus, indirectly draws attention to the rising demand for AI literacy and the necessary systemic process of its development. The conceptualisation level in the development of AI literacy will be demanding not only from procedural and technological but also legislative and legal aspects. Unexpected social and ecological effects have been insufficiently investigated so far, and recently, the potential social, economic and ecological risks of AI might have been overlooked. The increase in these risks is related to the increased interconnectedness among people, machines and socio-ecological systems.

Asrifan et al. (2025) examined the importance of AI literacy for eliminating these reported risks and ensuring certainty, increasing ethical awareness and informed decision-making. According to the authors, AI literacy should include a comprehensive understanding of AI principles, including machine learning, data governance and algorithmic ethics, allowing users to engage with AI technologies in various sectors and perceive the environmental demands of AI.

Kong et al. (2023) emphasised the importance of promoting AI literacy in the educated population and critically highlighted that research on effective AI literacy programmes' contents is insufficient. According to the authors, AI literacy represents a multi-conceptual framework consisting of multiple dimensions, including users' ethical awareness.

Ooi et al. (2023) explored the dynamic field of AI applications, including GenAI, and pointed to the need for a strategic, multi-level approach to increasing AI literacy. They did not explicitly focus on AI literacy in relation to the energy intensity of AI, but the ethical dimension in the proposed AI literacy strategies may consist of these aspects via their integration. Adnan et al. (2024) argued that research on the environmental impacts of AI and big data is still in its infancy and that the societal benefits of AI may support the achievement of sustainable development goals that may not be in line with environmental sustainability. The number of electronic devices used via AI has raised considerably, increasing serious concerns about environmental risks. Hence, building a trustworthy AI ecosystem is necessary.

Scantamburlo et al. (2024) observed that public perception of AI is inappropriate because it is based on a lack of understanding of AI technologies and their impact, a lack of relationships between AI technologies and policy initiatives, and a low level of interest in increasing AI literacy. Supporting AI literacy is one of the key factors in building a trustworthy AI ecosystem.

While AI literacy systems are important for enhancing the perception and evaluation of the environmental aspects of GenAI, other supporting mechanisms, which can quantify and compare many environmental aspects of AI and thus improve the use of AI literacy effects, are also important for improving awareness, trust and acceptance of AI. In this context, Gupta et al. (2024) drew attention to the effects of new metrics and methodologies that should facilitate public acceptance of green AI and pointed to awareness of sustainable practices in the AI life cycle.

Green AI projects that support energy-efficient algorithms, environmentally friendly hardware design and clean performance in AI infrastructure can reduce the negative environmental impacts of AI models (Alzoubi & Mishra, 2024; Malkova, 2025). Stricter environmental regulation from government and regulatory authorities can also provide considerable support for green AI, which can also stimulate the development of green projects (Polyakov et al., 2021; Radavičius & Tvaronavičienė, 2022). Some authors explored strategies to diminish the ecological footprint of AI models (Wang et al., 2023; Chauhan et al., 2024) and the effectiveness of innovative green projects (Levický et al., 2022; Piccinetti et al., 2023). Sponsoring green projects can attract environmentally oriented supporters, investors and consumers and thus improve the image of these socially responsible entities. This will contribute to building trust and loyalty among institutions and stakeholders that prioritise environmental interests in the development and use of AI.

Recent technological development – including the large language model DeepSeek – is strong evidence of the importance of AI literacy development in relation to environmentalism, the AI energy consumption issue and trust in AI. DeepSeek has brought new insights into the AI sector development as well as its sustainability in relation to global environmental goals.

Future development of large language models regarding AI environmental sustainability

In 2023, the release of the large language model DeepSeek was announced. DeepSeek can redefine the technological landscape by making advanced capabilities accessible to insufficiently represented communities while strongly promoting not only ethical but also inclusive innovation (Peng et al., 2025; Sallam et al., 2025). This openness also brings many existential risks. At the same time, the release of DeepSeek has generated strong discussions about the computational and energy demands of GenAI (Normile, 2025).

Conventional thinking based on the premise that building the biggest and best new AI models requires much hardware – and hence, energy – has been overturned by DeepSeek. DeepSeek models require considerably less energy to achieve the same performance as the other models with similar performance. This fundamentally changes the focus of AI development from model performance to resource efficiency, while many experts state that it has occurred earlier than expected (Roumeliotis et al., 2025). However, the increased efficiency of large language models may not automatically lead to a reduction in overall energy consumption as AI experts fear that innovations related to DeepSeek, through their everyday integration into computing, will support its greater development (Parmar & Govindarajulu, 2025). This is also based on the advantages of DeepSeek itself; for instance, unlike DeepSeek, the ChatGPT code in its new models is closed-source, that is, not publicly available for replication or use by others. DeepSeek lowers the barriers to entry for start-ups and supports competition and AI democratisation (Krause, 2025). Technological enterprises that will be inspired by the DeepSeek approach can create their own similar low-cost models; thus, the assumptions for decreasing energy consumption in the future are completely lost. Several experts predict that even if DeepSeek has achieved energy efficiency, it will not reduce the overall energy consumption of GenAI as much as the AI sector had expected in the long term (Gupta, 2025).

AI enterprises have begun to spend more on training models and, hence, to consume more energy because it brings them higher profit. Thus, the development of more intelligent models is limited primarily by enterprises' financial resources (O'Donnell, 2025). Therefore, regarding DeepSeek's rise, a more intense discussion has begun at many expertise levels about the energy consumption of AI and its further development conditioned by energy intensity and sustainability (Cappendijk et al., 2024).

Many technology studies published by the Massachusetts Institute of Technology Review call for a more detailed examination of the energy costs of DeepSeek and similar models that will play a significant role in the decision-making processes related to the development of GenAI in the near future (O'Donnell, 2025). These aspects have been already explored by Jagannadharao et al. (2023), who created an overview of the trade-offs between emission reduction and operational load while calling for the need for progressive development of carbon-sensitive computing. Many other studies have also drawn attention to the important issue of exploring sustainable computing and supporting the creation of environmentally aware strategies for training large language models (Liu et al., 2024; Gupta, 2025;).

These aspects are crucial in defining the main goal of this study and designing this research, which it is considered critical to investigate public awareness of the AI environmental aspects that may play a decisive role in the development, adoption and implementation of GenAI tools in the future. The study outcomes also support the development of a platform for an AI literacy system, which, in the conditions of the development of massive AI models, will play a key role in adopting AI tools in countries' digital ecosystem and thus gaining decisive competitive power on a global scale.

Research formulation

The review of the research studies presented is clear evidence of their considerable fragmentation, which is related to their target setting as well as to the defined research framework and other specific research parameters. This reduces their comparative potential, mainly owing to their methodological and data heterogeneity as well as the causal relationships investigated. The common elements of these studies are the appeal for a systematic investigation of the perception of environmental issues in the field of technological development and the assignment of new roles to users of AI tools as subjects influencing the sustainability of AI tools and technologies development. Many research studies have pointed to the strong potential of AI literacy systems and their future role in changing user behaviour.

Based on the literature review, the following research questions are formulated:

- research question 1: What are the Czech population's relations between use of GenAI and perception of climate change?
- research question 2: How willing is the Czech population to accept a change in behaviour owing to the environmental impact of data centres or GenAI in the digital media ecosystem?
- research question 3: What is the relationship between AI literacy and declared behavioural change owing to the environmental demand of GenAI?

This paper comprises six sections. Firstly, the Introduction addresses the discussed field of AI as a high technology of the future. Secondly, the literature review offers the theoretical background for all three research questions structured according to them with their formulation at its end. Thirdly, the Data and Methodology section describes the data set and the employed methodological techniques, whose outcomes are demonstrated in the fourth analytical section, which is also built according to the research questions. Fifthly, the Discussion compares the obtained findings with other research studies. Finally, the Conclusion summarises all the outcomes and makes suggestions for future research.

Data and methodology

Data

The data set encompassed several groups of examined questions from the questionnaire. The interviewees responded to four groups of statements.

The following questions were included in the first group:

- AI1: How often do you currently use the ChatGPT system?
- AI2: Have you tried the Gemini system based on AI?
- AI3: Have you tried the Microsoft Copilot system based on AI?
- AI4: Have you tried the Midjourney system based on AI?
- AI5: Have you tried the DALL-E system based on AI?
- AI6: Have you tried the Stability AI system based on AI?
- AI7: Have you tried the Wombo AI system based on AI?
- AI8: Have you tried the Canva system based on AI?
- AI9: Have you tried the Synthesis system based on AI?
- AI10: Have you tried the Murf AI system based on AI?

The possible responses to the first question were very often, often, sometimes and not currently, while the responses to the remaining questions were yes or no.

The second group of questions was related to environmental issues:

- E1: How important is solving the climate change issue for you personally?
- E2: Choose one of the following statements related to climate change that is the closest one to your attitude.
- E3: How well do you know what a data centre is and what it serves for?
- E4: After learning more details about the environmental impact of technology enterprises' data-centre operations, how willing would you be to take the next steps?

The first question was answered on a scale of 1 to 7, with the lowest value showing the highest importance and the highest value showing the lowest importance.

For the second question, the respondents could select among the following options:

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

The third environmental question was answered on a four-point scale, where the respondents selected the following options:

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

The fourth environmental question E4 was answered on a seven-point scale, with the lowest value meaning to be very willing and the highest value meaning to be very reluctant to take the following steps:

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

The third group of the questions is related to the use of the social networks:

- SN1: How often do you use social networks, where you have created your own profile and share posts – photos and videos (for instance, Facebook, X, Instagram, TikTok, Snapchat)?
- SN2: How often do you use the communication platforms that allow to exchange messages and multimedia files (for instance, WhatsApp, Messenger, Telegram Messenger, Signal, iMessage, Rakuten Viber, Kik Messenger, and so on)?

The responses to these questions are on a seven-level scale, while the individual levels represent more times per day, once per day, more times per week – two to six times per week, once per week, less often than once a week and at least once a quarter, less often than once per quarter, not at all.

The fourth group represents the four series of the statements, a total of the thirty-nine statements related to the various fields of the personal perception of AI.

The first series of the statements expresses the internal personal motivation and self-confidence in learning and includes the following nine statements:

- SA1: Artificial intelligence is important in my everyday life (for instance, personal life, working life).
- SA2: I like to study the field of AI.
- SA3: Self-education in the field of AI enriches my life.
- SA4: I am interested in discovering new AI technologies.
- SA5: I believe that I am able to perform tasks related to AI.
- SA6: I am sure that I am able to handle projects related to AI well.
- SA7: I believe that I can gain the knowledge and skills related to AI.
- SA8: I am sure I will achieve good result in AI tests.
- SA9: I am convinced that I understand AI.

The second series of the statements demonstrates the interest in career and self-confidence in AI use and includes the following ten statements:

- SB1: Knowledge of AI will help me find a good job in the future.
- SB2: Knowledge of AI will give me an advantage in my future career.
- SB3: Understanding AI will contribute to my future profession.
- SB4: My future career will include AI.
- SB5: In my work, I will use skills in the field of problem solving using AI.
- SB6: I am able to use tools related to AI well.
- SB7: I am sure that I am able to perform activities involving the use of AI.
- SB8: I believe that I am able to perform tasks related to the involvement of AI.
- SB9: I believe that I will learn to understand the fundamental AI concepts.
- SB10: I believe that I am able to choose suitable applications of AI to solve problems.

The third series of the statements is related to the behavioural aspects and includes the following eleven statements:

- SC1: I will continue to use AI in the future.
- SC2: I will try to keep up with the latest technologies in the field of AI.
- SC3: In the future, I plan to devote time to explore new features of AI applications.
- SC4: I actively participate in educational activities focused on AI.
- SC5: I am passionate about studying materials about AI.
- SC6: I learn effectively while completing tasks.
- SC7: I often look for other materials about AI such as books or magazines in my free time.
- SC8: I often try to explain the teaching material about AI to my classmates, colleagues, or friends.
- SC9: I try to collaborate with classmates, colleagues, or friends to complete tasks and projects focused on AI.
- SC10: In my free time, I often discuss AI with classmates, colleagues, or friends.
- SC11: When I run into a problem in the activities related to AI, I usually ask classmates, colleagues, or friends for help.

The fourth series of the statements is related to the cognitive aspects and evaluation and includes the following nine statements:

- SD1: I know what AI is and I remember its definitions.
- SD2: I know how to use AI applications (for instance, Siri, chatbots).
- SD3: I know some of the fundamental principles of how AI works (for instance, linear model, decision tree, machine learning).
- SD4: I understand how AI perceives the world (for instance, seeing, hearing) to solve various tasks.
- SD5: I am able to compare different concepts of AI (for instance, deep learning, machine learning).
- SD6: I am able to apply AI to solve problems.
- SD7: I am able to create a machine learning model to solve problems.
- SD8: I am able to solve problems through involving AI (for instance, chatbots, robotics).
- SD9: I am able to evaluate applications and concepts of AI for different situations.

Each of the listed statements is answered on a seven-level scale from

1 to 7, while the lowest value represents strong agreement and the highest value means strong disagreement to the particular statement.

Inspiration for construction of the above-listed questions comes from several studies – questioning data centre attitudes (Seth, 2024) and the statements about AI (Gursoy et al., 2019; Yigitcanlar et al., 2024).

Methodology

The data set was collected through an online survey conducted by a professional surveying agency in the Czech Republic from 18 October 2024 to 23 October 2024. A total of 2710 respondents were addressed, of which 1268 returned the completed survey. Overall, 1252 questionnaires were answered by respondents aged over 18 years. The respondents' selection was based on a quota selection. Data collection was conducted through computer-assisted self-interviewing via website populace.cz and was supervised by the agency Ipsos. The average period for answering the questionnaire was about 30 min. The main methodological technique for analytical processing in this study was regression analysis (Galton, 1989), specifically logistic regression. To adopt this technique, testing was performed. A chi-squared test was employed to reveal the distribution state of the input data (Kenney, 1939; Pearson, 1893) and uncover inner relationships between the examined variables. Confidence intervals were determined at a level of 95 %. A five-per-cent statistical significance threshold was employed to evaluate the determined hypotheses. Robustness was checked via the information criteria – namely, the Akaike information criterion and the Bayesian information criterion. All analytical procedures were conducted in the R software environment (R Core Team, 2024).

Regarding the visualisation of the analytical outcomes in the following section, highlighting particular cells in shades of grey via shading, the darker the grey colour, the more statistically significant the outcome. That is, only statistically not significant outcomes remain in white colour, and all highlighted cells represent statistically significant outcomes. The levels of statistical significance visualised are four – 10 %, 5 %, 1 %, and 0.1 %. In the case of the Akaike information criterion and Bayesian information criterion, highlighting was performed in a similar way, meaning the darker the shade, the more suitable the outcome. Here, the values are sorted from the highest value – that is, the darkest shade to the lowest value, which is the lightest shade.

Analysis

The analytical section comprises three subsections based on the individual RQs. Each subsection is divided into the testing and modelling phase.

Perception of climate change

The RQ 1 is linked to the Czech population's relations between the use of GenAI and perception of climate change. Four questions from the questionnaire are interconnected: frequency of ChatGPT current use, use of the other GenAI systems, personal importance of the climate change solution and period of climate change. Table 1 demonstrates the systems testing and their relationships to the respondents' environmental attitudes.

As visualised by Table 1, every examined system meets the criterion of random distribution of probability with a large margin itself. Moreover, the general question related to frequency of ChatGPT use shows the same outcome. Regarding the relationship between the particular GenAI systems and the importance of solving the climate change issue, outcomes vary. While the relationships between the use of Google Gemini, Microsoft Copilot and Canva and the importance of solving the climate change issue are assigned random distribution of probability, other systems, among which are Midjourney, DALL-E, Stability AI, Wombo AI, Synthesis and Murf AI, demonstrate bias that requires further investigation. However, from the perspective of the relationship

Table 1
Perception of climate change testing.

System	chi-square test		chi-square test to E1		chi-square test to E2	
	Statistic	p-value	Statistic	p-value	Statistic	p-value
AI1	$6.69 . 10^{1}$	$1.98 . 10^{-14}$	$1.84 . 10^{1}$	$4.29 . 10^{-1}$	$9.90 . 10^{0}$	$6.25 . 10^{-1}$
AI2	$6.60 . 10^{2}$	$1.69 . 10^{-145}$	$1.94 . 10^{1}$	$3.60 . 10^{-3}$	$7.90 . 10^{0}$	$9.54 . 10^{-2}$
AI3	$4.81 . 10^{2}$	$1.53 . 10^{-106}$	$2.31 . 10^{1}$	$7.64 . 10^{-1}$	$8.56 . 10^{0}$	$7.31 . 10^{-2}$
AI4	$9.14 . 10^{2}$	$8.66 . 10^{-201}$	$7.61 . 10^{0}$	$2.68 . 10^{-1}$	$9.40 . 10^{0}$	$5.19 . 10^{-2}$
AI5	$9.07 . 10^{2}$	$2.58 . 10^{-199}$	$7.32 . 10^{0}$	$2.92 . 10^{-1}$	$8.89 . 10^{0}$	$6.38 . 10^{-2}$
AI6	$1.03 . 10^{3}$	$6.92 . 10^{-226}$	$1.18 . 10^{1}$	$6.67 . 10^{-2}$	$1.74 . 10^{1}$	$1.65 . 10^{-3}$
AI7	$1.07 . 10^{3}$	$1.39 . 10^{-234}$	$6.71 . 10^{0}$	$3.48 . 10^{-1}$	$7.22 . 10^{0}$	$1.25 . 10^{-1}$
AI8	$7.40 . 10^{2}$	$6.23 . 10^{-163}$	$2.35 . 10^{1}$	$6.55 . 10^{-4}$	$1.05 . 10^{1}$	$3.23 . 10^{-2}$
AI9	$1.10 . 10^{3}$	$5.18 . 10^{-241}$	$6.36 . 10^{0}$	$3.84 . 10^{-1}$	$1.10 . 10^{1}$	$2.65 . 10^{-2}$
AI10	$1.11 . 10^{3}$	$2.93 . 10^{-244}$	$3.93 . 10^{0}$	$6.86 . 10^{-1}$	$1.08 . 10^{1}$	$2.90 . 10^{-2}$

Source: Own elaboration by the authors.

between the systems and the climate-change impact period, more systems carry bias. While Google Gemini, Microsoft Copilot, Midjourney, DALL-E and Wombo AI show random distribution of probability, Stability AI, Canva, Synthesis and Murf AI point to certain bias. All systems demonstrating random distribution only slightly overstep a five-per-cent statistical significance threshold with the exception of Wombo AI, which oversteps a ten-per-cent statistical significance threshold to a little extent. Conversely, Canva, Synthesis and Murf reach a statistical significance threshold of almost 5 %. From both perspectives, these outcomes need to be further investigated.

The analytical outcomes demonstrate the following findings. The frequency of use of ChatGPT has an impact on the perception of the importance of solving climate change. Other GenAI systems show that for Google Gemini, Microsoft Copilot and Canva, no relation exists between the frequency of use of ChatGPT and the perception of the importance of solving climate change. Other systems, such as Midjourney, DALL-E, Stability AI, Wombo AI, Synthesis and Murf AI, are not determined in this field. An examination of the relationship between the frequency of use of ChatGPT and all studied GenAI systems with the climate change periods shows that the frequency of use of Google Gemini, Microsoft Copilot, Midjourney, DALL-E and Wombo AI does not affect the perception of the expected climate change.

The regression models are offered in the subsequent tables, beginning with the frequency of ChatGPT use to the importance of the climate change issue logistic regression model in Table 2.

As seen in Table 2, the importance of the climate-change issue is modelled via the frequency of ChatGPT use. Respondents who use ChatGPT often see the importance of the climate change issue at a lower level and vice versa. The odds that respondents who use ChatGPT often consider the climate-change issue less important are 9.62 % higher. Thus, the odds that respondents who use ChatGPT only sometimes consider the climate-change issue less important are 16.53 % higher. Finally, the odds that respondents who do not use currently ChatGPT consider the climate-change issue less important are 19.83 % higher. These outcomes show a visible inverse proportion, that is, the more often the respondents use ChatGPT, the less they consider the climate-change issue important.

Table 3 demonstrates the relationship between frequency of ChatGPT use and the climate-change impact period via the logistic regression model.

Table 3 shows a clear pattern. Respondents who use ChatGPT often see the climate-change impact period further in the future, meaning the

Table 2
The frequency of ChatGPT use to the importance of the climate-change issue regression model.

Frequency	Variable	Estimation			Confidence interval	
		Coefficient	Standard error	p-value	Lower boundary	Upper boundary
often	intercept	2.1868	0.3377	0.0205	1.1282	4.2387
	E1	1.0962	0.1039	0.3764	0.8943	1.3438
sometimes	intercept	2.4064	0.3283	0.0075	1.2644	4.5799
	E1	1.1653	0.1003	0.1273	0.9573	1.4185
not currently	intercept	1.5203	0.3460	0.2260	0.7716	2.9951
	E1	1.1983	0.1040	0.0819	0.9774	1.4692

Source: Own elaboration by the authors.

Table 3
The frequency of ChatGPT use to the climate-change impact period regression model.

Frequency	Variable	Estimation			Confidence interval	
		Coefficient	Standard error	p-value	Lower boundary	Upper boundary
often	intercept	2.2662	0.3511	0.0198	1.1389	4.5093
	E2	1.0985	0.1290	0.4665	0.8531	1.4145
sometimes	intercept	2.3907	0.3422	0.0109	1.2225	4.6751
	E2	1.2012	0.1246	0.1412	0.9409	1.5334
not currently	intercept	1.5197	0.3612	0.2466	0.7486	3.0849
	E2	1.2392	0.1297	0.0981	0.9611	1.5977

Source: Own elaboration by the authors.

climate change is not happening yet, and vice versa. The odds that respondents who use ChatGPT often consider the climate-change impact period later in the future are 9.85 % higher. The odds that respondents who use ChatGPT only sometimes see the climate-change impact period later in the future are 20.12 % higher. Finally, respondents who do not currently use ChatGPT consider the climate-change impact to happen in the future, with odds 23.92 % higher. The outcomes demonstrate that the more often the respondents use ChatGPT, the later they see climate change happening.

Environmental impact of data centres

The RQ 2 is based on the Czech population's willingness to accept a change in behaviour owing to the environmental impact of data centres or GenAI in the digital media ecosystem. It includes a mixture of six interconnected environmental and sociological questions. With regard to the previously examined importance of climate-change issue perception and climate-change impact period, two other questions investigating sharing via social networks and communicating via various platforms are added.

The matrix of the testing outcome of the relationships between environmental and social network attitudes is offered in Table 4.

Table 4 represents a matrix whose lower half demonstrates test statistics values and upper half p-values. From an individual evaluation point of view, all environmental and social network questions are assigned random distribution of probability. Regarding the mutual pairs of the tested questions, the frequency of ChatGPT use demonstrates more occasions of biased distribution. Its relationship to the importance of solving the climate-change issue, the climate-change impact period, as well as the data centre purpose and sharing on the social networks' profiles point to biased relationships. All other pairs demonstrate random distribution of probability, with the exception of the pair involving the climate-change impact period and frequency of online communication, whose p-value of $6.45 . 10^{-2}$ stands only slightly over a statistical significance threshold of 5 %.

The analytical outcomes show interesting findings. No statistically significant relationship is found between the respondents' answers to the questions about knowledge and the use of data centres in relation to the frequency of ChatGPT use, perception of the climate-change importance, and expected climate-change period. Moreover, such a relationship does not exist between the frequency of ChatGPT use and the frequency of social networks use. The same is applied to the frequency of use of communication platforms that enable sharing messages and multimedia. Conversely, a statistically significant relationship between the perception of climate-change importance and the frequency of use of ChatGPT, social networks and communication platforms. A statistically significant relationship exists between the frequency of ChatGPT use and the frequency of use of social networks and communication platforms. These outcomes also confirm no relationship between the frequency of use of social networks and the frequency of use of communication platforms.

The modelling phase of the second question follows with the five statements tied to the frequency of ChatGPT use. The first one devoted to changing email address is illustrated by

Table 5.

The decision to change email address to another provider after learning more details about the environmental impact of technology companies' data-centre operation is demonstrated in

Table 4
Testing the environmental impact in the digital media ecosystem.

	E1	E2	E3	AI1	SN1	SN2
E1	$2.28 . 10^{2}$	$3.45 . 10^{-112}$	$5.89 . 10^{-3}$	$4.29 . 10^{-1}$	$1.03 . 10^{-2}$	$1.27 . 10^{-2}$
E2	$6.04 . 10^{2}$	$8.16 . 10^{1}$	$1.98 . 10^{-6}$	$6.25 . 10^{-1}$	$3.59 . 10^{-3}$	$6.45 . 10^{-2}$
E3	$3.66 . 10^{1}$	$4.91 . 10^{1}$	$2.26 . 10^{2}$	$9.81 . 10^{-3}$	$7.66 . 10^{-3}$	$9.42 . 10^{-5}$
AI1	$1.84 . 10^{1}$	$9.90 . 10^{\circ}$	$2.17 . 10^{1}$	$6.69 . 10^{1}$	$2.28 . 10^{-1}$	$4.69 . 10^{-1}$
SN1	$5.85 . 10^{1}$	$4.68 . 10^{1}$	$3.57 . 10^{1}$	$2.21 . 10^{1}$	$1.35 . 10^{3}$	$1.35 . 10^{-95}$
SN2	$5.75 . 10^{1}$	$3.53 . 10^{1}$	$4.94 . 10^{1}$	$1.78 . 10^{1}$	$5.62 . 10^{2}$	$2.01 . 10^{3}$
p-value	$1.76 . 10^{-46}$	$8.15 . 10^{-17}$	$1.18 . 10^{-48}$	$1.98 . 10^{-14}$	$2.61 . 10^{-288}$	$0.00 . 10^{\circ}$

Source: Own elaboration by the authors.

Table 5
The frequency of ChatGPT use to changing email address regression model.

Frequency	Variable	Estimation			Confidence interval	
		Coefficient	Standard error	p-value	Lower boundary	Upper boundary
often	intercept	2.6359	0.4472	0.0302	1.0971	6.3331
	E4.1	1.0329	0.1814	0.8582	0.7239	1.4738
sometimes	intercept	1.6520	0.4430	0.2572	0.6933	3.9361
	E4.1	1.4054	0.1754	0.0524	0.9965	1.9820
not currently	intercept	1.0020	0.4695	0.9967	0.3993	2.5145
	E4.1	1.4774	0.1833	0.0333	1.0315	2.1162

Source: Own elaboration by the authors.

Table 5. The table shows an indirect dependence, meaning the lower the frequency of ChatGPT use, the higher the odds of being reluctant to change email address to another provider. Respondents who use ChatGPT often have 3.29 % higher odds of being reluctant to change email address to another provider. The odds 40.54 % higher for respondents who use ChatGPT sometimes and 47.74 % higher for respondents who do not currently use ChatGPT. The low frequency of ChatGPT use indicates the respondents' lower willingness to change email address provider.

The second question, which addresses the transfer of one's own data to an energy-efficient cloud provider, is offered in Table 6.

Table 6 demonstrates the outcomes of the regression model representing the relationship of the frequency of ChatGPT use and transferring own data to an energy-efficient cloud provider. It shows an almost indirect dependence, meaning that the lower the frequency of ChatGPT use, the higher the odds of being reluctant to transfer own data to an energy-efficient cloud provider. Respondents who use ChatGPT often have 13.44 % higher odds of being reluctant to transfer own data to more energy-efficient provider. These odds are 27.46 % higher for respondents who use ChatGPT sometimes and 24.62 % higher for respondents who do not currently use ChatGPT. These outcomes demonstrate that the low frequency of ChatGPT use indicates the respondents' lower willingness to transfer own data to a more energy-efficient provider.

The third question, which addresses leaving a favourite social network that does not use an energy-efficient data centre, is shown in Table 7.

Table 7 illustrates the regression model demonstrating the relationship between frequency of ChatGPT use and leaving a favourite social network that does not use an energy-efficient data centre. Overall, a clear indirect dependence is exemplified, meaning the lower the frequency of ChatGPT use, the higher the odds of being reluctant to leave a favourite social network that does not use an energy-efficient data centre. Respondents who use ChatGPT often have 2.75 % higher odds of being reluctant to leave a favourite social network that does not use an energy-efficient data centre. These odds are 14.86 % higher for respondents who use ChatGPT sometimes and 32.39 % higher for respondents who do not currently use ChatGPT. The listed outcomes enable to formulate the conclusion that the low frequency of ChatGPT use demonstrates a lower tendency for the respondents to leave social a network that does not use an energy-efficient data centre.

The fourth question, which addresses the situation in which one stop using a favourite streaming platform that does not use energy-efficient data centres, is shown in Table 8.

The regression model visualised in Table 8 offers the outcomes of the regression model representing the relationship of the frequency of ChatGPT use and stopping the use of a favourite streaming platform that does not use energy-efficient data centres. All in all, it shows a partial indirect dependence, meaning that the lower the frequency of ChatGPT use, the lower the odds of being reluctant to stop using a favourite streaming platform that does not use energy-efficient data centres. Respondents who use ChatGPT often have 17.31 % lower odds of being reluctant to stop using a favourite streaming platform that does not use energy-efficient data centres. These odds are 2.40 % lower for respondents who use ChatGPT sometimes and 5.54 % for respondents who do not currently use ChatGPT. Thus, the low frequency of ChatGPT use demonstrates a higher tendency for the respondents to leave their favourite streaming platform that does not use an energy-efficient data centre.

The fifth question, which addresses the situation in which one stops using a favourite AI system that does not use an energy-efficient data centre, is revealed in Table 9.

Table 9 demonstrates the relationship between the frequency of ChatGPT use and stopping the use of a favourite GenAI system that does not use energy-efficient data centres. Altogether, it illustrates a direct dependence, denoting that the lower the frequency of ChatGPT use, the lower the odds of being reluctant to stop using a favourite GenAI system that does not use an energy-efficient data centre. Respondents who use ChatGPT often are assigned 4.62 % lower odds of being reluctant to stop using a favourite GenAI system that does not use energy-efficient data centres. These odds are 6.05 % lower for respondents who use ChatGPT sometimes and 14.39 % lower for respondents who do not currently use ChatGPT. Thus, the low frequency of ChatGPT use demonstrates a higher tendency for the respondents to leave a favourite streaming platform that does not use an energy-efficient data centre. The low frequency of ChatGPT use indicates a higher willingness of the respondents to stop using a favourite GenAI system that does not use an energy-efficient data centre.

Behavioural change

The RQ 3 investigates the relationship between AI literacy and

Table 6
The frequency of ChatGPT use to transferring own data to an energy-efficient cloud provider regression model.

Frequency	Variable	Estimation			Confidence interval	
		Coefficient	Standard error	p-value	Lower boundary	Upper boundary
often	intercept	2.1467	0.4741	0.1071	0.8476	5.4370
	E4.2	1.1344	0.2009	0.5304	0.7651	1.6819
sometimes	intercept	2.1778	0.4610	0.0914	0.8823	5.3758
	E4.2	1.2746	0.1943	0.2117	0.8710	1.8651
not currently	intercept	1.5874	0.4826	0.3383	0.6165	4.0876
	E4.2	1.2462	0.2027	0.2775	0.8377	1.8539

Source: Own elaboration by the authors.

Table 7
The frequency of ChatGPT use to leaving a favourite social network that does not use an energy-efficient data centre regression model.

Frequency	Variable	Estimation			Confidence interval	
		Coefficient	Standard error	p-value	Lower boundary	Upper boundary
often	intercept	2.6581	0.4984	0.0498	1.0008	7.0599
	E4.3	1.0275	0.1940	0.8889	0.7025	1.5027
sometimes	intercept	2.6817	0.4851	0.0420	1.0364	6.9389
	E4.3	1.1486	0.1875	0.4599	0.7954	1.6586
not currently	intercept	1.2866	0.5153	0.6248	0.4686	3.5321
	E4.3	1.3239	0.1961	0.1526	0.9014	1.9444

Source: Own elaboration by the authors.

Table 8
The frequency of ChatGPT use to stopping the use of a favourite streaming platform that does not use energy-efficient data centres regression model.

Frequency	Variable	Estimation			Confidence interval	
		Coefficient	Standard error	p-value	Lower boundary	Upper boundary
often	intercept	4.5171	0.4936	0.0023	1.7167	11.8860
	E4.4	0.8269	0.1850	0.3045	0.5754	1.1885
sometimes	intercept	4.0058	0.4822	0.0040	1.5569	10.3066
	E4.4	0.9760	0.1781	0.8914	0.6884	1.3837
not currently	intercept	3.0049	0.5028	0.0287	1.1216	8.0505
	E4.4	0.9446	0.1864	0.7598	0.6556	1.3611

Source: Own elaboration by the authors.

Table 9
The frequency of ChatGPT use to stopping the use of a favourite AI system that does not use energy-efficient data centres regression model.

Frequency	Variable	Estimation			Confidence interval	
		Coefficient	Standard error	p-value	Lower boundary	Upper boundary
often	intercept	3.1818	0.4998	0.0206	1.1946	8.4744
	E4.5	0.9538	0.1922	0.8055	0.6544	1.3901
sometimes	intercept	4.3807	0.4834	0.0022	1.6984	11.2989
	E4.5	0.9395	0.1859	0.7370	0.6525	1.3526
not currently	intercept	3.7572	0.5030	0.0085	1.4019	10.0699
	E4.5	0.8571	0.1953	0.4300	0.5845	1.2570

Source: Own elaboration by the authors.

declared behavioural change owing to the environmental demand of GenAI. It includes four statements expressing various attitudes of the respondents.

Firstly, behavioural change owing to the environmental demand of GenAI is illustrated in Table 10.

Behavioural change as shown in Table 10 is interpreted in a homogeneous way. All statements' relationships to the general question related to the frequency of ChatGPT use and use of Gemini and Microsoft Copilot align with random distribution of probability. This points to homogeneity of the respondents' responses in this field and opens up space for further investigation.

The following subsections are devoted to the particular examined fields of the questioned statements –internal personal motivation and self-confidence in learning, interest in career and self-confidence when using AI, behavioural aspects, and cognitive aspects and evaluation.

Internal personal motivation and self-confidence in learning

As seen in Table 15 in the appendix, the respondents' environmental attitudes towards internal personal motivation and self-confidence in learning show considerable differences. The first group of attitudes is associated with the possibility of changing one's own email address or going to the email service provider that uses more energy-efficient and water-cooled data centres. Respondents who agree with the usefulness of learning about AI in personal life, study and work, have 16.75 % higher odds of being reluctant to change email address to another provider. These odds are 17.47 % higher for respondents who enjoy education in the field of AI and 20.42 % higher for those who think that self-education in the field of AI enriches their life. Respondents who are interested in discovering new AI technologies have 17.95 % higher odds. These odds are 15.91 % higher for respondents who believe that they can perform tasks related to AI. Those who are sure to be able to conduct projects related to AI have 13.22 % higher odds. Respondents who believe that they can gain knowledge and skills associated with AI are more reluctant by 15.72 %. Respondents who are sure that they will achieve good results in AI tests have 18.74 % higher odds of being reluctant to achieve good results in AI tests; these odds are 17.05 % higher for respondents who are convinced that they understand AI.

The second group of attitudes represents the possibility of transferring one's own data to a provider that uses more energy-efficient and water-cooled data centres. Respondents who agree with the usefulness of learning about AI in personal life, study and work have 24.52 % higher odds of being reluctant to transfer their own data to another provider. Additionally, respondents who enjoy education in the field of AI are assigned 23.50 % higher odds. Those who think that self-education in the field of AI enriches their life are more reluctant by 24.32 %, and those who are interested in discovering new AI technologies by 23.28 %. These odds are 21.56 % higher for respondents who believe that they can perform tasks related to AI. The ones who are sure to be able to conduct projects related to AI have 19.22 % higher odds, and those who believe to be able to gain knowledge and skills associated with AI are more reluctant by 21.25 %. Respondents, who are sure that will achieve good results in AI tests have 20.44 % higher odds of being reluctant to achieve good results in AI tests. Respondents who are convinced that they understand AI have 17.77 % higher odds.

The third group of attitudes demonstrates the possibility of leaving a favourite social network that does not use energy-efficient and water-

Table 10
Testing of behavioural change owing to the environmental demand of GenAI.

Statement	chi-square test to AI1		chi-square test to AI2		chi-square test to AI3	
	Statistic	p-value	Statistic	p-value	Statistic	p-value
SA1	$5.67 \cdot 10^{1}$	$7.02 \cdot 10^{-6}$	$6.85 \cdot 10^{1}$	$8.28 \cdot 10^{-13}$	$8.90 \cdot 10^{1}$	$4.90 \cdot 10^{-17}$
SA2	$9.46 \cdot 10^{1}$	$2.15 \cdot 10^{-12}$	$1.60 \cdot 10^{2}$	$5.12 \cdot 10^{-32}$	$1.76 \cdot 10^{2}$	$2.24 \cdot 10^{-35}$
SA3	$8.97 \cdot 10^{1}$	$1.64 \cdot 10^{-11}$	$1.47 \cdot 10^{2}$	$3.81 \cdot 10^{-29}$	$1.50 \cdot 10^{2}$	$8.19 \cdot 10^{-30}$
SA4	$9.11 \cdot 10^{1}$	$9.10 \cdot 10^{-12}$	$1.44 \cdot 10^{2}$	$1.19 \cdot 10^{-28}$	$1.73 \cdot 10^{2}$	$1.24 \cdot 10^{-34}$
SA5	$6.79 \cdot 10^{1}$	$1.01 \cdot 10^{-7}$	$1.47 \cdot 10^{2}$	$3.37 \cdot 10^{-29}$	$1.29 \cdot 10^{2}$	$1.87 \cdot 10^{-25}$
SA6	$6.97 \cdot 10^{1}$	$5.01 \cdot 10^{-8}$	$1.29 \cdot 10^{2}$	$2.46 \cdot 10^{-25}$	$1.32 \cdot 10^{2}$	$4.21 \cdot 10^{-26}$
SA7	$6.98 \cdot 10^{1}$	$4.93 \cdot 10^{-8}$	$1.37 \cdot 10^{2}$	$5.42 \cdot 10^{-27}$	$1.33 \cdot 10^{2}$	$3.06 \cdot 10^{-26}$
SA8	$6.34 \cdot 10^{1}$	$5.76 \cdot 10^{-7}$	$1.26 \cdot 10^{2}$	$9.34 \cdot 10^{-25}$	$1.23 \cdot 10^{2}$	$3.27 \cdot 10^{-24}$
SA9	$6.90 \cdot 10^{1}$	$6.66 \cdot 10^{-8}$	$1.36 \cdot 10^{2}$	$6.21 \cdot 10^{-27}$	$1.01 \cdot 10^{2}$	$1.64 \cdot 10^{-19}$
SB1	$6.39 \cdot 10^{1}$	$4.75 \cdot 10^{-7}$	$1.25 \cdot 10^{2}$	$1.85 \cdot 10^{-24}$	$1.32 \cdot 10^{2}$	$5.85 \cdot 10^{-26}$
SB2	$8.02 \cdot 10^{1}$	$7.92 \cdot 10^{-10}$	$1.03 \cdot 10^{2}$	$5.78 \cdot 10^{-20}$	$1.21 \cdot 10^{2}$	$8.62 \cdot 10^{-24}$
SB3	$7.58 \cdot 10^{1}$	$4.59 \cdot 10^{-9}$	$1.21 \cdot 10^{2}$	$1.15 \cdot 10^{-23}$	$1.22 \cdot 10^{2}$	$6.66 \cdot 10^{-24}$
SB4	$1.00 \cdot 10^{2}$	$2.05 \cdot 10^{-13}$	$1.21 \cdot 10^{2}$	$7.98 \cdot 10^{-24}$	$1.48 \cdot 10^{2}$	$1.72 \cdot 10^{-29}$
SB5	$1.09 \cdot 10^{2}$	$5.16 \cdot 10^{-15}$	$1.53 \cdot 10^{2}$	$2.00 \cdot 10^{-30}$	$1.53 \cdot 10^{2}$	$1.64 \cdot 10^{-30}$
SB6	$8.66 \cdot 10^{1}$	$5.83 \cdot 10^{-11}$	$1.55 \cdot 10^{2}$	$7.76 \cdot 10^{-31}$	$1.55 \cdot 10^{2}$	$7.00 \cdot 10^{-31}$
SB7	$7.60 \cdot 10^{1}$	$4.28 \cdot 10^{-9}$	$1.49 \cdot 10^{2}$	$1.24 \cdot 10^{-29}$	$1.67 \cdot 10^{2}$	$1.54 \cdot 10^{-33}$
SB8	$6.81 \cdot 10^{1}$	$9.49 \cdot 10^{-8}$	$1.38 \cdot 10^{2}$	$2.15 \cdot 10^{-27}$	$1.41 \cdot 10^{2}$	$5.24 \cdot 10^{-28}$
SB9	$3.72 \cdot 10^{1}$	$4.92 \cdot 10^{-3}$	$1.21 \cdot 10^{2}$	$8.98 \cdot 10^{-24}$	$1.30 \cdot 10^{2}$	$1.16 \cdot 10^{-25}$
SB10	$5.72 \cdot 10^{1}$	$5.65 \cdot 10^{-6}$	$1.34 \cdot 10^{2}$	$2.02 \cdot 10^{-26}$	$1.42 \cdot 10^{2}$	$4.63 \cdot 10^{-28}$
SC1	$1.24 \cdot 10^{2}$	$7.71 \cdot 10^{-18}$	$1.53 \cdot 10^{2}$	$1.91 \cdot 10^{-30}$	$2.10 \cdot 10^{2}$	$1.73 \cdot 10^{-42}$
SC2	$9.06 \cdot 10^{1}$	$1.12 \cdot 10^{-11}$	$1.73 \cdot 10^{2}$	$1.19 \cdot 10^{-34}$	$2.04 \cdot 10^{2}$	$2.24 \cdot 10^{-41}$
SC3	$8.49 \cdot 10^{1}$	$1.17 \cdot 10^{-10}$	$1.36 \cdot 10^{2}$	$5.93 \cdot 10^{-27}$	$1.64 \cdot 10^{2}$	$9.81 \cdot 10^{-33}$
SC4	$8.15 \cdot 10^{1}$	$4.62 \cdot 10^{-10}$	$1.32 \cdot 10^{2}$	$5.60 \cdot 10^{-26}$	$1.56 \cdot 10^{2}$	$3.34 \cdot 10^{-31}$
SC5	$1.19 \cdot 10^{2}$	$5.91 \cdot 10^{-17}$	$1.82 \cdot 10^{2}$	$1.50 \cdot 10^{-36}$	$1.55 \cdot 10^{2}$	$7.61 \cdot 10^{-31}$
SC6	$5.35 \cdot 10^{1}$	$2.23 \cdot 10^{-5}$	$1.36 \cdot 10^{2}$	$7.18 \cdot 10^{-27}$	$1.34 \cdot 10^{2}$	$1.49 \cdot 10^{-26}$
SC7	$7.09 \cdot 10^{1}$	$3.19 \cdot 10^{-8}$	$1.35 \cdot 10^{2}$	$1.22 \cdot 10^{-26}$	$1.17 \cdot 10^{2}$	$6.73 \cdot 10^{-23}$
SC8	$6.73 \cdot 10^{1}$	$1.27 \cdot 10^{-7}$	$1.48 \cdot 10^{2}$	$2.55 \cdot 10^{-29}$	$1.15 \cdot 10^{2}$	$1.74 \cdot 10^{-22}$
SC9	$7.48 \cdot 10^{1}$	$6.79 \cdot 10^{-9}$	$1.48 \cdot 10^{2}$	$2.50 \cdot 10^{-29}$	$1.20 \cdot 10^{2}$	$1.57 \cdot 10^{-23}$
SC10	$7.05 \cdot 10^{1}$	$3.77 \cdot 10^{-8}$	$1.34 \cdot 10^{2}$	$1.50 \cdot 10^{-26}$	$1.16 \cdot 10^{2}$	$1.43 \cdot 10^{-22}$
SC11	$5.80 \cdot 10^{1}$	$4.30 \cdot 10^{-6}$	$6.83 \cdot 10^{1}$	$9.23 \cdot 10^{-13}$	$4.91 \cdot 10^{1}$	$7.26 \cdot 10^{-9}$
SD1	$4.81 \cdot 10^{1}$	$1.45 \cdot 10^{-4}$	$1.12 \cdot 10^{2}$	$8.16 \cdot 10^{-22}$	$1.16 \cdot 10^{2}$	$1.04 \cdot 10^{-22}$
SD2	$5.13 \cdot 10^{1}$	$4.74 \cdot 10^{-5}$	$1.69 \cdot 10^{2}$	$5.98 \cdot 10^{-34}$	$2.13 \cdot 10^{2}$	$2.84 \cdot 10^{-43}$
SD3	$6.47 \cdot 10^{1}$	$3.44 \cdot 10^{-7}$	$1.31 \cdot 10^{2}$	$7.24 \cdot 10^{-26}$	$1.40 \cdot 10^{2}$	$9.74 \cdot 10^{-28}$
SD4	$5.75 \cdot 10^{1}$	$5.11 \cdot 10^{-6}$	$1.22 \cdot 10^{2}$	$5.59 \cdot 10^{-24}$	$1.19 \cdot 10^{2}$	$2.27 \cdot 10^{-23}$
SD5	$5.56 \cdot 10^{1}$	$1.04 \cdot 10^{-5}$	$1.32 \cdot 10^{2}$	$5.29 \cdot 10^{-26}$	$1.13 \cdot 10^{2}$	$5.66 \cdot 10^{-22}$
SD6	$8.76 \cdot 10^{1}$	$3.86 \cdot 10^{-11}$	$1.94 \cdot 10^{2}$	$4.14 \cdot 10^{-39}$	$2.10 \cdot 10^{2}$	$1.18 \cdot 10^{-42}$
SD7	$5.77 \cdot 10^{1}$	$4.81 \cdot 10^{-6}$	$1.28 \cdot 10^{2}$	$2.80 \cdot 10^{-25}$	$7.69 \cdot 10^{1}$	$1.60 \cdot 10^{-14}$
SD8	$6.63 \cdot 10^{1}$	$1.91 \cdot 10^{-7}$	$1.41 \cdot 10^{2}$	$7.66 \cdot 10^{-28}$	$1.53 \cdot 10^{2}$	$2.24 \cdot 10^{-30}$
SD9	$7.73 \cdot 10^{1}$	$2.53 \cdot 10^{-9}$	$1.52 \cdot 10^{2}$	$2.40 \cdot 10^{-30}$	$1.43 \cdot 10^{2}$	$2.57 \cdot 10^{-28}$

Source: Own elaboration by the authors.

saving opportunities in its data centre. Respondents who agree with usefulness of learning about AI in personal life, study and work have 11.62 % higher odds of being reluctant to transfer own data to another provider. Furthermore, respondents who enjoy education in the field of AI have odds higher than 9.78 %. Those who think that self-education in the field of AI enriches their life are more reluctant by 11.10 %, and those who are interested in discovering new AI technologies by 12.74 %. These odds are 9.74 % higher for respondents who believe that they can perform tasks related to AI. Those who are sure to be able to conduct projects related to AI have 8.46 % higher odds. Respondents who believe to be able to gain knowledge and skills associated with AI are more reluctant by 7.97 %. Respondents, who are sure that will achieve good results in AI tests have 12.44 % higher odds of being reluctant to achieve good results in AI tests; those who are convinced that they understand AI have 8.50 % higher odds.

The fourth group of attitudes shows the possibility of stopping the use of a favourite streaming platform that does not use energy-efficient and water-saving opportunities in its data centres. Respondents who agree with the usefulness of learning about AI in personal life, study and work have 14.93 % higher odds of being reluctant to stop using a favourite streaming platform that does not use energy-efficient and water-saving opportunities in its data centres. Moreover, respondents who enjoy education in the field of AI have 7.32 % higher odds. The ones who think that self-education in the field of AI enriches their life are more reluctant by 10.67 %. Those who are interested in discovering new AI technologies have 8.93 % higher odds. Respondents who believe that they can perform tasks related to AI have 8.96 % higher odds. Those who are sure to be able to conduct projects related to AI have 6.77 % higher odds. Respondents who believe that they can gain knowledge and skills associated with AI are more reluctant by 4.77 %. Respondents who are sure that will achieve good results in AI tests have 10.06 % higher odds of being reluctant to achieve good results in AI tests; those who are convinced that they understand AI have 7.85 % higher odds.

The fifth group of attitudes shows the possibility of stopping the use of a favourite GenAI platform that does not use energy-efficient and water-saving opportunities in its data centres. Respondents who agree with the usefulness of learning about AI in personal life, study and work have 16.65 % higher odds of being reluctant to stop using a favourite streaming platform that does not use energy-efficient and water-saving opportunities in its data centres. Moreover, respondents who enjoy education in the field of AI have 9.68 % higher odds. Those who think that self-education in the field of AI enriches their life are more reluctant by 11.40 %. Those who are interested in discovering new AI technologies have 11.06 % higher odds. These odds are 6.08 % higher for respondents who believe that they can perform tasks related to AI. Those who think that they can conduct projects related to AI have 6.16 % higher odds. Respondents who believe that they can gain knowledge and skills associated with AI are more reluctant by 6.23 %. Respondents who are sure that will achieve good results in AI tests have 6.91 % higher odds of being reluctant to achieve good results in AI tests; those who are convinced that they understand AI have 5.80 % higher odds.

Interest in career and self-confidence when using AI

The interest in career and self-confidence when using AI is represented by the second subsection of the regression models. In the appendix, Table 16 demonstrates the respondents' attitudes towards the five observed steps in the 10 statements related to their career and self-confidence. The first group of attitudes is associated with the possibility of changing one's own email address or going to the email service provider that uses more energy-efficient and water-cooled data centres. Respondents who think that knowledge of AI will help them find a good job in the future have 17.05 % higher odds of being reluctant to change email address to another provider. Additionally, respondents who agree that knowledge of AI will give them an advantage in their future career have 17.30 % higher odds. There odds are 16.14 % higher for respondents who think that understanding AI will contribute to their future profession. Those who think that their future career will include AI are more reluctant by 14.09 %. Respondents who believe that they will use skills in the field of problem-solving using AI in their work have 15.76 % higher odds. Respondents who believe that they can use tools related to AI well have 18.38 % higher odds. Those who think that they can perform activities involving the use of AI have 15.37 % higher odds. Respondents who believe that they can perform tasks related to the involvement of AI are more reluctant by 15.78 %. Those who believe that they will learn to understand the fundamental AI concepts have 14.76 % higher odds of being reluctant to achieve good results in AI tests. Respondents who believe that they can choose suitable applications of AI to solve problems have 15.43 % higher odds.

The second group of attitudes are related to the possibility of transferring one's own data to a provider that uses more energy-efficient and water-cooled data centres. Respondents who think knowledge of AI will help them find a good job in the future have 21.85 % higher odds of being reluctant to change email address to another provider. Moreover, respondents who agree that knowledge of AI will give them an advantage in their future career have 23.88 % higher odds, and those who think that understanding AI will contribute to their future profession have 25.29 % higher odds. Respondents who think that their future career will include AI are more reluctant by 20.23 %. Those who believe that they will use skills in the field of problem-solving using AI in their work have 21.34 % higher odds. These odds are 20.13 % higher for respondents who believe that they can use tools related to AI well. Those who think that they are sure they can perform activities involving the use of AI have 19.31 % higher odds. Respondents who believe that they can perform tasks related to the involvement of AI are more reluctant by 19.23 %. Respondents who believe that they will learn to understand the fundamental AI concepts have 25.12 % higher odds of being reluctant to achieve good results in AI tests; those who believe that they can choose suitable applications of AI to solve problems have 21.61 % higher odds.

The third group of attitudes is related to the possibility of leaving a favourite social network that does not use energy-efficient and water-saving opportunities in its data centres. Respondents who think knowledge of AI will help them to find a good job in the future have 11.81 % higher odds of being reluctant to change email address to another provider. Moreover, respondents who agree that knowledge of AI will give them an advantage in their future career have 11.43 % higher odds. Respondents who think that understanding AI will contribute to their future profession have 11.68 % higher odds. Those who think that their future career will include AI are 11.61 % more reluctant. Respondents who believe they will use skills in the field of problem-solving using AI in their work have 14.40 % higher odds. These odds are 11.38 % higher for respondents who believe that they can use tools related to AI well. Those who think that they can perform activities involving the use of AI have 9.27 % higher odds. Respondents who believe that they can perform tasks related to the involvement of AI are more reluctant by 7.56 %. Respondents who believe that they will learn to understand the fundamental AI concepts have 9.57 % higher odds of being reluctant to achieve good results in AI tests; those who believe that they can choose suitable applications of AI to solve problems have 8.77 % higher odds.

The fourth group of attitudes shows the possibility of stopping the use of a favourite streaming platform that does not use energy-efficient and water-saving opportunities in its data centres. Respondents who think that knowledge of AI will help them find a good job in the future have 12.51 % higher odds of being reluctant to change email address to another provider. Additionally, respondents who agree that knowledge of AI will give them an advantage in their future career have 11.30 % higher odds. These odds are 12.10 % higher for respondents who think that understanding AI will contribute to their future profession. Those who think that their future career will include AI are more reluctant by 11.94 %. Those who believe they will use skills in the field of problem-solving using AI in their work have 11.05 % higher odds. These odds are 8.80 % higher for respondents who believe that they can use tools related to AI well. Those who are sure to be able to perform activities involving the use of AI have 7.53 % higher odds. Respondents who believe that they can perform tasks related to the involvement of AI are more reluctant by 8.11 %. Respondents who believe that they will learn to understand the fundamental AI concepts have 10.16 % higher odds of being reluctant to achieve good results in AI tests; those who believe that they can choose suitable applications of AI to solve problems have 7.70 % higher odds.

The fifth group of attitudes shows the possibility of stopping the use of a favourite GenAI platform that does not use energy-efficient and water-saving opportunities in its data centres. Respondents who think that knowledge of AI will help them to find a good job in the future have 11.45 % higher odds of being reluctant to change email address to another provider. Furthermore, respondents who agree that knowledge of AI will give them an advantage in their future career have 9.68 % higher odds. These odds are 9.46 % higher for respondents who think that understanding AI will contribute to their future profession. Those who think that their future career will include AI are more reluctant by 10.11 %. Those who believe they will use skills in the field of problem-solving using AI in their work have 9.94 % higher odds. These odds are 7.24 % higher for respondents who believe that they can use tools related to AI well. Those who think that they can perform activities involving the use of AI have 6.49 % higher odds. Respondents who believe that they can perform tasks related to the involvement of AI are more reluctant by 5.69 %. Respondents who believe that they will learn to understand the fundamental AI concepts have 10.24 % higher odds of being reluctant to achieve good results in AI tests; those who believe that they can choose suitable applications of AI to solve problems have 5.11 % higher odds.

Behavioural aspects

The third subsection is devoted to the behavioural aspects. In the appendix, Table 17 demonstrates the outcomes of the regression models for the five observed steps in the 11 statements related to the behavioural aspects. The first group of attitudes is associated with the possibility of changing one's own email address or going to the email service provider that uses more energy-efficient and water-cooled data centres. Respondents who will continue to use AI in the future have 15.11 % higher odds of being reluctant to change email address to another provider. Additionally, respondents who try to keep up with the latest technologies in the field of AI have 16.45 % higher odds. These odds are 17.38 % higher for respondents who plan to devote time to explore new features of AI applications in the future. Those who actively participate in educational activities focused on AI are more reluctant by 22.41 %. Respondents who are passionate about AI-related materials have 22.05 % higher odds. These odds are 18.16 % higher for respondents who learn effectively while completing tasks. Those who often look for other materials about AI, such as books or magazines, in their own free time have 27.47 % higher odds. Respondents who often try to explain the teaching material about AI to their classmates, colleagues or friends are more reluctant by 24.75 %. Respondents who try to collaborate with classmates, colleagues or friends to complete tasks and projects focused on AI have 18.19 % higher odds of being reluctant to achieve good results in AI tests. Respondents who often discuss AI with classmates, colleagues or friends in their free time have 25.51 % higher odds. The odds are 25.23 % higher for respondents who usually ask classmates, colleagues or friends for help when they run into a problem in the activities related to AI.

The second group of attitudes is related to the possibility of transferring one's own data to a provider that uses more energy-efficient and water-cooled data centres. Respondents who will continue to use AI in the future have 20.62 % higher odds of being reluctant to change email address to another provider. Additionally, respondents who try to keep up with the latest technologies in the field of AI have 23.57 % higher odds. Respondents who plan to devote time to explore new features of AI applications in the future have 20.58 % higher odds. Those who actively participate in educational activities focused on AI are more reluctant by 20.10 %. Respondents who are passionate about studying materials about AI have 17.45 % higher odds, and those who learn effectively while completing tasks have 22.55 % higher odds. Those who often look for other materials about AI, such as books or magazines, in their own free time have 19.16 % higher odds. Respondents who often try to explain the teaching material about AI to their classmates, colleagues or friends are more reluctant by 16.80 %. Respondents who try to collaborate with classmates, colleagues or friends to complete tasks and projects focused on AI have 13.90 % higher odds of being reluctant to achieve good results in AI tests; those who often discuss AI with classmates, colleagues or friends in their free time have 19.02 % higher odds. Respondents who usually ask classmates, colleagues or friends for help when they run into a problem in the activities related to AI have 21.79 % higher odds.

The third group of attitudes is related to the possibility of leaving a favourite social network that does not use energy-efficient and water-saving opportunities in its data centres. Respondents who will continue to use AI in the future have 8.28 % higher odds of being reluctant to change email address to another provider. Moreover, respondents who will try to keep up with the latest technologies in the field of AI have 11.11 % higher odds. Respondents who plan to devote time to explore new features of AI applications in the future have 13.46 % higher odds. Those who actively participate in educational activities focused on AI are more reluctant by 21.99 %. Respondents who are passionate about studying materials about AI have 18.79 % higher odds. Respondents who learn effectively while completing tasks have 14.33 % higher odds. Those who often look for other materials about AI, such as books or magazines, in their own free time have 24.33 % higher odds. Respondents who often try to explain the teaching material about AI to my classmates, colleagues or friends, are more reluctant by 19.91 %. Respondents who try to collaborate with classmates, colleagues or friends to complete tasks and projects focused on AI have 14.78 % higher odds of being reluctant to achieve good results in AI tests. Respondents who often discuss AI with classmates, colleagues or friends in their free time have 13.81 % higher odds. Respondents who usually ask classmates, colleagues or friends for help when they run into a problem in the activities related to AI have 18.30 % higher odds.

The fourth group of attitudes shows the possibility of stopping the use of a favourite streaming platform that does not use energy-efficient and water-saving opportunities in its data centres. Respondents who will continue to use AI in the future have 5.93 % higher odds of being reluctant to change email address to another provider. Moreover, respondents who will try to keep up with the latest technologies in the field of AI have 9.89 % higher odds. Respondents who plan to devote time to explore new features of AI applications in the future have 9.47 % higher odds. Those who actively participate in educational activities focused on AI are more reluctant by 14.91 %. Those who are passionate about studying materials about AI have 12.27 % higher odds.

Respondents who learn effectively while completing tasks have 12.52 % higher odds. Those who often look for other materials about AI, such as books or magazines, in their own free time, have 17.57 % higher odds. Respondents who often try to explain the teaching material about AI to their classmates, colleagues or friends, are 13.42 % more reluctant. Respondents who try to collaborate with classmates, colleagues or friends to complete tasks and projects focused on AI have 12.05 % higher odds of being reluctant to achieve good results in AI tests. Respondents who often discuss AI with classmates, colleagues or friends in their free time have 11.88 % higher odds. Respondents who usually ask classmates, colleagues or friends for help when they run into a problem during the activities related to AI have 16.41 % higher odds.

The fifth group of attitudes shows the possibility of stopping the use of a favourite GenAI platform that does not use energy-efficient and water-saving opportunities in its data centres. Respondents who will continue to use AI in the future have 7.91 % higher odds of being reluctant to change email address to another provider. Moreover, respondents who will try to keep up with the latest technologies in the field of AI have 12.09 % higher odds. Respondents who plan to devote time to explore new features of AI applications in the future have 9.38 % higher odds. Those who actively participate in educational activities focused on AI are more reluctant by 10.85 %. Those who are passionate about studying materials about AI have 7.19 % higher odds. These odds are 8.86 % higher for respondents who learn effectively while completing tasks. Those who often look for other materials about AI, such as books or magazines, in their own free time have 11.67 % higher odds. Respondents who often try to explain the teaching material about AI to their classmates, colleagues or friends are more reluctant by 9.61 %. Respondents who try to collaborate with classmates, colleagues or friends to complete tasks and projects focused on AI have 9.41 % higher odds of being reluctant to achieve good results in AI tests. Respondents who often discuss AI with classmates, colleagues or friends in their free time have 10.75 % higher odds. Respondents who usually ask classmates, colleagues or friends for help when they run into a problem in the activities related to AI have 14.36 % higher odds.

Cognitive aspects and evaluation

The fourth subsection is devoted to the cognitive aspects and evaluation. In the appendix, Table 18 demonstrates the outcomes of the regression models for the five observed steps in the nine statements related to the cognitive aspects and evaluation. The first group of attitudes is associated with the possibility of changing one's own email address or going to the email service provider that uses more energy-efficient and water-cooled data centres. Respondents who know what AI is and remember its definitions have 16.94 % higher odds of being reluctant to change email address to another provider. Moreover, respondents who know how to use AI applications (for instance, Siri, chatbots) have 9.30 % higher odds. Respondents who know some of the fundamental principles of how AI works (for instance, linear model, decision tree, machine learning) have higher odds. Those who understand how AI perceives the world (for instance, seeing, hearing) to solve various tasks are more reluctant by 21.59 %. Respondents who can compare different concepts of AI (for instance, deep learning, machine learning) have 21.54 % higher odds. Respondents who can apply AI to solve problems have 14.57 % higher odds. Those who can create a machine-learning model to solve problems have 25.52 % higher odds. Respondents who can solve problems through AI (for instance, chatbots, robotics) have 17.21 % higher odds. Respondents who can evaluate applications and concepts of AI for different situations have 19.60 % higher odds of being reluctant to achieve good results in AI tests.

The second group of the attitudes is related to the possibility of transferring one's own data to a provider that uses more energy-efficient and water-cooled data centres. Respondents who know what AI is and remember its definitions have 21.69 % higher odds of being reluctant to change email address to another provider. Moreover, respondents who know how to use AI applications (for instance, Siri, chatbots) have 17.77 % higher odds. Respondents who know some of the fundamental principles of how AI works (for instance, linear model, decision tree, machine learning) have 14.19 % higher odds. Those who understand how AI perceives the world (for instance, seeing, hearing) to solve various tasks are more reluctant by 17.89 %. Respondents who can compare different concepts of AI (for instance, deep learning, machine learning) have 14.30 % higher odds. Respondents who can apply AI to solve problems have odds higher by 16.62 %. Those who can create a machine-learning model to solve problems have 16.13 % higher odds. Respondents who can solve problems through AI (for instance, chatbots, robotics) are more reluctant by 19.06 %. Respondents who can evaluate applications and concepts of AI for different situations have 18.05 % higher odds of being reluctant to achieve good results in AI tests.

The third group of attitudes is related to a possibility of leaving a favourite social network that does not use energy-efficient and water-saving opportunities in its data centres. Respondents who know what AI is and remember its definitions have 10.35 % higher odds of being reluctant to change email address to another provider. Furthermore, respondents who know how to use AI applications (for instance, Siri, chatbots) have 6.97 % higher odds. Respondents who know some of the fundamental principles of how AI works (for instance, linear model, decision tree, machine learning) have 13.16 % higher odds. Those who understand how AI perceives the world (for instance, seeing, hearing) to solve various tasks are more reluctant by 12.28 %. Respondents who can compare different concepts of AI (for instance, deep learning, machine learning) have 14.41 % higher odds. Respondents who can apply AI to solve problems have 8.24 % higher odds. Those who can create a machine-learning model to solve problems have 15.53 % higher odds. Respondents who can solve problems through AI (for instance, chatbots, robotics) are more reluctant by 8.94 %. Respondents who can evaluate applications and concepts of AI for different situations have 11.61 % higher odds of being reluctant to achieve good results in AI tests.

The fourth group of attitudes shows the possibility of stopping the use of a favourite streaming platform that does not use energy-efficient and water-saving opportunities in its data centres. Respondents who know what AI is and remember its definitions have 11.85 % higher odds of being reluctant to change email address to another provider. Additionally, respondents who know how to use AI applications (for instance, Siri, chatbots) have 5.55 % higher odds. Respondents who know some of the fundamental principles of how AI works (for instance, linear model, decision tree, machine learning) have 9.66 % higher odds. Those who understand how AI perceives the world (for instance, seeing, hearing) to solve various tasks are more reluctant by 11.17 %. Respondents who can compare different concepts of AI (for instance, deep learning, machine learning) have 12.28 % higher odds. Respondents who can apply AI to solve problems have 5.78 % higher odds. Those who can create a machine-learning model to solve problems have 14.94 % higher odds. Respondents who can solve problems through AI (for instance, chatbots, robotics) are more reluctant by 9.29 %. Respondents who can evaluate applications and concepts of AI for different situations have 11.56 % higher odds of being reluctant to achieve good results in AI tests.

The fifth group of attitudes shows the possibility of stopping the use of a favourite GenAI platform that does not use energy-efficient and water-saving opportunities in its data centres. Respondents who know what AI is and remember its definitions have 14.45 % higher odds of being reluctant to change email address to another provider. Moreover, respondents who know how to use AI applications (for instance, Siri, chatbots) have 4.75 % higher odds. Respondents who know some of the fundamental principles of how AI works (for instance, linear model, decision tree, machine learning) have 7.07 % higher odds. Those who understand how AI perceives the world (for instance, seeing, hearing) to solve various tasks are more reluctant by 10.14 %. Respondents who can compare different concepts of AI (for instance, deep learning, machine learning) have 8.51 % higher odds. Respondents who are able to apply AI to solve problems have 4.40 % higher odds. Those who can create a machine-learning model to solve problems have 7.04 % higher odds. Respondents who can solve problems by involving AI (for instance, chatbots and robotics) are 5.20 % more reluctant. Respondents who can evaluate applications and concepts of AI for different situations have 6.55 % higher odds of being reluctant to achieve good results in AI tests.

Robustness check

Several methods were employed to verify the robustness of the techniques applied in the analytical processing: firstly, the Akaike information criterion to evaluate the significance of the constructed regression models, and second, the Bayesian information criterion. These two information criteria are focused on the comparative perspective of the constructed regression models. The lower their value, the better the interpretation power is assigned to a particular regression model. Regarding the first research question dealing with the perception of climate change, different considerations apply.

Table 11 offers the information criteria' values for the regression models that demonstrate the frequency of ChatGPT use in relation to the attitude to climate change and the climate-change impact period.

For both information criteria as seen in Table 11, the latter regression model signifying the climate change impact period has the better interpretation power. Nevertheless, both constructed regression models are assigned values of high information quality regarding the other examined regression models.

Table 12 shows the information criteria values for the regression models that demonstrate energy-efficient and water-saving opportunities.

As seen in Table 12, the ranking of the explored regression models according to the employed information criteria is identical, showing consistency of the obtained analytical outcomes. Furthermore, all the analytical processes for the option related to changing one's own email address or going to the email service provider that uses more energy-efficient and water-cooled data centres have the best interpretation power. On the other side of the ranking, the option related to stopping the use of a favourite GenAI platform that does not use energy-efficient and water-saving opportunities in its data centres stands.

Table 13 explores the Akaike information criterion for the statements' regression models.

Table 14 explores the Bayesian information criterion for the statements' regression models.

Table 13 and Table 14 show a high consistency level for both information criteria related to the statements' regression models. Moreover, a pattern related to the particular statements, rather than to the individual E4 options, is visible here. This means that the respondents do not perceive the E4 options more differently than the statements, towards which their attitudes are demonstrated. This may be due to their understanding of the points questioned in the questionnaire as a standard common user does not differentiate the listed particular options so well. Another reason can be found in the current use of online services. Many users perceive the questioned services as a whole, meaning their responses are too close to distinguish the nuances of the questioned points. Nevertheless, minor distinctions are visible, and the analytical outcomes introduce an interesting view of the explored field.

Robustness is confirmed via both employed information values, secured through the input heterogeneity of the implemented analytical techniques. The statistical significance levels are high enough to evaluate performed logistic regression analysis as of high interpretation power. The regression models, which are assigned p-values above a statistical significance threshold, can be perceived as supplementary to illustrate the overall situation of the respondents' attitudes.

Table 11
The Akaike information criterion values for the climate change regression models.

AI1	Attitude to the climate change	
	E1	E2
AIC	1149.159	1149.232
BIC	1173.666	1173.739

Source: Own elaboration by the authors.

Table 12
The Akaike information criterion values for the energy-efficient and water-saving opportunities regression models.

AI1	Attitude to the energy-efficient and water-saving opportunities				
	E4.1	E4.2	E4.3	E4.4	E4.5
AIC	1141.551	1151.163	1149.344	1151.116	1152.334
BIC	1166.058	1175.670	1173.851	1175.623	1176.841

Source: Own elaboration by the authors.

Table 13
The Akaike information criterion values for the statements' regression models.

Statement	Environmental attitude				
	E4.1	E4.2	E4.3	E4.4	E4.5
SA1	1738.806	1693.274	1748.478	1725.655	1694.408
SA2	1735.201	1694.332	1751.362	1739.825	1708.953
SA3	1727.201	1692.779	1749.117	1734.462	1706.018
SA4	1732.676	1693.355	1744.685	1737.042	1705.939
SA5	1742.628	1705.911	1752.671	1738.313	1714.735
SA6	1748.845	1713.027	1754.738	1741.282	1714.727
SA7	1743.701	1707.865	1755.447	1743.229	1714.688
SA8	1736.632	1710.356	1748.410	1736.973	1714.003
SA9	1740.447	1716.839	1754.703	1740.010	1715.096
SB1	1735.674	1698.749	1746.969	1729.954	1705.262
SB2	1733.665	1689.361	1747.190	1731.993	1708.268
SB3	1736.932	1683.668	1746.519	1730.073	1708.621
SB4	1743.104	1703.106	1747.002	1730.807	1707.634
SB5	1739.318	1700.559	1740.797	1733.121	1708.259
SB6	1736.038	1709.510	1749.710	1738.449	1713.384
SB7	1742.496	1710.154	1752.876	1739.919	1714.044
SB8	1741.778	1710.750	1755.509	1739.198	1714.956
SB9	1744.589	1693.544	1752.647	1736.129	1708.903
SB10	1743.001	1704.574	1753.894	1739.868	1715.560
SC1	1739.832	1700.615	1753.338	1741.311	1711.288
SC2	1738.344	1694.450	1748.924	1735.751	1704.401
SC3	1735.299	1703.869	1743.524	1736.369	1709.445
SC4	1720.421	1706.467	1719.848	1725.129	1707.079
SC5	1724.156	1715.747	1731.710	1732.067	1713.260
SC6	1734.158	1699.149	1742.147	1730.842	1710.624
SC7	1704.814	1710.449	1713.804	1719.240	1705.984
SC8	1714.765	1717.095	1728.047	1729.473	1709.720
SC9	1734.128	1723.479	1741.129	1731.950	1709.806
SC10	1713.212	1711.793	1744.262	1732.904	1707.994
SC11	1706.352	1697.945	1728.825	1719.352	1698.165
SD1	1740.284	1705.875	1751.742	1733.620	1701.524
SD2	1753.631	1710.074	1755.449	1741.786	1715.453
SD3	1741.960	1722.158	1744.428	1736.161	1713.054
SD4	1724.908	1714.042	1747.229	1733.980	1708.791
SD5	1726.111	1723.480	1743.048	1732.204	1711.574
SD6	1742.788	1715.596	1753.932	1741.767	1715.947
SD7	1716.514	1720.642	1741.651	1727.707	1713.779
SD8	1735.509	1708.549	1752.731	1736.626	1715.184
SD9	1731.769	1714.218	1748.792	1733.474	1714.034

Source: Own elaboration by the authors.

Table 14
The Bayesian information criterion values for the statements' regression models.

Statement	Environmental attitude				
	E4.1	E4.2	E4.3	E4.4	E4.5
SA1	1749.098	1703.566	1758.770	1735.947	1704.700
SA2	1745.493	1704.624	1761.654	1750.117	1719.245
SA3	1737.493	1703.071	1759.409	1744.754	1716.310
SA4	1742.968	1703.647	1754.977	1747.334	1716.231
SA5	1752.920	1716.203	1762.963	1748.605	1725.027
SA6	1759.137	1723.319	1765.030	1751.574	1725.019
SA7	1753.993	1718.157	1765.739	1753.521	1724.980
SA8	1746.924	1720.648	1758.702	1747.265	1724.295
SA9	1750.739	1727.131	1764.995	1750.302	1725.388
SB1	1745.966	1709.041	1757.261	1740.246	1715.554
SB2	1743.957	1699.653	1757.482	1742.285	1718.560
SB3	1747.224	1693.960	1756.811	1740.365	1718.913
SB4	1753.396	1713.398	1757.294	1741.099	1717.926
SB5	1749.610	1710.851	1751.089	1743.413	1718.551
SB6	1746.330	1719.802	1760.002	1748.741	1723.676
SB7	1752.788	1720.446	1763.168	1750.211	1724.336
SB8	1752.070	1721.042	1765.801	1749.490	1725.248
SB9	1754.881	1703.836	1762.939	1746.420	1719.195
SB10	1753.293	1714.866	1764.186	1739.868	1725.852
SC1	1750.124	1710.907	1763.630	1751.603	1721.580
SC2	1748.636	1704.742	1759.216	1746.043	1714.693
SC3	1745.591	1714.161	1753.816	1746.661	1719.737
SC4	1730.713	1716.759	1730.140	1735.421	1717.371
SC5	1734.448	1726.039	1742.002	1742.359	1723.552
SC6	1744.450	1709.441	1752.439	1741.134	1720.916
SC7	1715.106	1720.741	1724.096	1729.532	1716.276
SC8	1725.057	1727.387	1738.339	1739.765	1720.012
SC9	1744.420	1733.771	1751.421	1742.242	1720.098
SC10	1723.504	1722.085	1754.554	1743.196	1718.286
SC11	1716.824	1708.237	1739.117	1729.644	1708.457
SD1	1750.576	1716.167	1762.034	1743.912	1711.816
SD2	1763.923	1720.366	1765.741	1752.078	1725.745
SD3	1752.252	1732.450	1754.720	1746.453	1723.346
SD4	1735.200	1724.334	1757.521	1744.272	1719.083
SD5	1736.403	1733.772	1753.340	1742.496	1721.866
SD6	1753.080	1725.888	1764.224	1752.059	1726.239
SD7	1726.806	1730.934	1751.943	1737.999	1724.071
SD8	1745.801	1718.841	1763.023	1746.918	1725.476
SD9	1741.769	1724.510	1759.084	1743.766	1724.326

Source: Own elaboration by the authors.

Discussion

Overall, AI has brought interesting shifts to investigating the population and understanding the examined fields of everyday life. The following discussion is structured according to the RQs. Subsequently, the limitations of this research are offered, in addition to the policy implications and trajectories for policymaking processes.

Evaluation of the perception of climate change

Regarding the RQ 1 focused on the Czech population's relations between GenAI use and perception of climate change, specific GenAI systems show some differences. Whereas the use of Google Gemini, Microsoft Copilot and Canva cannot be predicted based on the respondents' attitudes towards climate change and its solving, the use of Midjourney, DALL-E, Stability AI, Wombo AI, Synthesis and Murf AI is influenced by the observed relations.

The analytical outcomes reveal several key findings. At first, the frequency of ChatGPT use appears to influence individuals' perception of the importance of solving climate change. However, for GenAI systems such as Google Gemini, Microsoft Copilot and Canva, no relation is found between the frequency of ChatGPT use and the perception of the climate-change issue. Other GenAI systems such as Midjourney, DALL-E, Stability AI, Wombo AI, Synthesis and Murf AI are evaluated in this context, showing bias. The exploration of the relationship between the frequency of ChatGPT use and climate-change perceptions across all explored GenAI systems shows that the frequency of use of Google Gemini, Microsoft Copilot and Canva does not impact perceptions of future climate change. Additionally, the outcomes show a clear inverse proportion as the respondents using GenAI systems more frequently perceive climate change as less important. The data indicate that increased use of the GenAI systems is associated with the diminished importance of climate-change solving.

Many of these aspects are also explained by the outcomes of recent research studies. Norhayati Rafida and Norailis (2024), in their study of environmental communication within AI tools, confirmed that the way in which AI is perceived and applied significantly influences the development of environmental and social problems as well as the solutions offered. Agathokleous et al. (2023) highlighted the advantages of ChatGPT and its power to influence biology and environmental science but also mentioned some limitations, such as the provision of inaccurate and misleading information to the public by nonexperts. ChatGPT can provide a large amount of environmental information, including scientific and research papers, but it cannot properly cite the references used to generate outputs and make files available for download. As confirmed by Wu et al. (2024), Khowaja et al. (2024), and many others, ChatGPT and large language models are constantly improving and will be able to increasingly influence the environmental attitudes of people that use AI communication tools for this purpose. Another finding is that the inverse relationship between higher frequency of use of AI systems and perception of climate change may be related to the ChatGPT use scenario confirmed by Yang and Wang (2024), who stated that the population's perception and attitudes towards ChatGPT are influenced by the effects of this tool's use scenarios. AI is constantly being trained and will require human assistance to understand data – especially on specific and more professionally demanding topics. Developers should pay close attention to continuously improve information and transparency of responses in a relation to the different population groups and their forms of use of AI tools.

Evaluating the environmental impact of data centres

The RQ 2 is focused on the environmental impact of data centres. The five observed procedures are investigated via the frequency of ChatGPT use – the steps described in the E4 question. Overall, the analytical outcomes reveal several important findings.

Firstly, this study explored the change in email address provider. Here, the essential outcome shows that the low frequency of ChatGPT use indicates the respondents' lower willingness to change the email address provider owing to more energy-efficient and water-cooled data centres. If the respondents use ChatGPT more frequently, the odds that they will be reluctant to change the email address provider are higher than 40 %.

Secondly, this study explored the transferring of one's own data. Generally, the low frequency of ChatGPT use points to the respondents' lower willingness to transfer their own data to a more energy-efficient provider. Users who use the ChatGPT more frequently have 24 % higher odds of transferring their own data to providers with more energy-efficient and water-cooled data centres.

Thirdly, leaving a favourite social network that does not use energy-efficient and water-saving opportunities in its data centres was examined. The elementary outcome represents the fact that the low frequency of ChatGPT use points to the respondents' lower inclination to leave a social network that does not use an energy-efficient data centre. Respondents who do not use ChatGPT have 32 % higher odds of not leaving their favourite social network that does not use energy-efficient and water-saving opportunities in its data centres.

Fourthly, stopping the use of a favourite streaming platform that does not use energy-efficient and water-saving opportunities in its data centres was investigated. Overall, the low frequency of ChatGPT use clues the respondents in leaving a favourite streaming platform that does not use an energy-efficient data centre. Although the odds levels are lower than in the previous cases, the pattern remains clearly visible here. Respondents who use ChatGPT often would have 17 % lower odds of being reluctant to stop using a favourite streaming platform that does not use energy-efficient data centres.

Fifthly, stopping the use of a favourite GenAI platform that does not use energy-efficient and water-saving opportunities in its data centres was observed. The outcome shows that the low frequency of ChatGPT use points to the respondents' higher willingness to stop using a favourite GenAI system that does not use energy-efficient data centres. The odds levels are slightly lower and partially similar to the fourth case on leaving a favourite social network; however, respondents who do not currently use ChatGPT have 14 % higher odds of being reluctant to stop to use a favourite GenAI system that does not use energy-efficient data centres.

Moreover, the question pairs consisting of environmental and social networks questions are assigned random distribution of probability, while those related to the frequency of ChatGPT use are more biased.

Altogether, no statistically significant relationship was found between the respondents' knowledge and use of data centres and the frequency of GenAI system use, the perceived importance of climate change or the expected period for solving climate change. Similarly, no such relationship exists between the use of the individual GenAI systems and the frequency of social network use or between the use of communication platforms for sharing messages and multimedia. Nonetheless, a statistically significant relationship was observed between the perceived importance of climate change and the frequency of GenAI systems, social network and communication platform use. Additionally, a statistically significant relationship was found between the frequency of GenAI systems use and that of social network and communication platform use. These outcomes also confirm no relationship between the frequency of social network use and that of communication platform use. The low frequency of ChatGPT usage is associated with a reduced willingness to change email provider among the respondents. This suggests that a lower frequency of ChatGPT use is associated with less interest in transferring data to more energy-efficient email providers. The findings also indicate that respondents who use ChatGPT less frequently are less likely to leave social networks that do not use energy-efficient data centres. Similarly, the low frequency of ChatGPT use is related to a higher tendency for the respondents to stop using a favourite streaming platform that does not maintain energy-efficient data centres. Finally, a partial conclusion is that respondents who use ChatGPT less frequently are more likely to discontinue using GenAI systems that do not rely on energy-efficient data centres.

The above-mentioned findings can be discussed on several levels, including in relation to the population's attitude towards AI tools and new technologies in general as well as to targeted manipulation and contrarianism in the issue of climate change on a national and global scale. This fact was also systematically analysed by Vasiljev (2024), who pointed to the power of conspiracy theories, serious risks of organised contrarianism and manipulative role of contrarians in creating resistance and anti-reflexive tendencies in accepting the agenda of climate programmes and environmental strategies. The population's low level of environmental literacy, reinforced by apathy towards progressive technological development and the introduction of AI technologies into everyday life, can support the systematic creation of resistance towards them. The population can more easily justify resistance or apathy towards AI with energy unsustainability, fears of an uncontrollable increase in energy costs and their impact on the general population and social security. Uncertainty, chaos and public distrust of the energy strategies related to development and AI use can deepen political and social polarisation and create serious social obstacles to implementing national strategies based on ecological sustainability and economic efficiency. In addition to contrarianism, climate disinformation has also become a major threat as it has a wide range of dissemination possibilities and, therefore, its timely detection and the public's protection from it can be increasingly difficult (Coan et al., 2021). Governments and their policies must reflect on these facts and sensitively capture all changes in the perception of environmental aspects when AI tools are used, as well as to reveal all the influences that affect changes in the population's attitudes towards climate strategies, along with trust in government institutions that promote the country's environmental policies.

The analytical findings confirm the strong variability of the responses in the different items related to AI use in population's everyday lives, creating a picture of the population's willingness to alter when adapting potential environmental policies and revealing factors that may influence changes in the population's attitudes.

Evaluation of behavioural change

Behavioural change is viewed via the five sets of statements as proposed by the RQ 3, according to which the discussion is also structured.

In the following subsections, only the cases with the highest odds are considered. All outcomes are listed in the appendix in Tables 15–18. Here, the three highest values related to a particular attitude of the respondents are listed for each group of statements in a descending way.

Changing own email address

Firstly, changing one's own email address is observed.

To be reluctant to change one's own email address or to go to the email service provider that uses more energy-efficient and water-cooled data centres is a characteristic with odds higher by:

- 27.47 % for respondents who often look for other materials about AI, such as books or magazines, in their own free time;
- 25.52 % for respondents who can create a machine-learning model to solve problems;
- 25.23 % for respondents who usually ask classmates, colleagues or friends for help when they run into a problem in activities related to AI;
- 25.21 % for respondents who often discuss AI with classmates, colleagues or friends in their free time;
- 21.59 % for respondents who understand how AI perceives the world (for instance, seeing, hearing) to solve various tasks;
- 21.54 % for respondents who can compare different concepts of AI (for instance, deep learning, machine learning);
- 20.42 % for respondents who think that self-education in the field of AI enriches their life;
- 18.74 % for respondents who are sure that they will achieve good results in AI tests, who would be more reluctant to achieve good results in AI tests;
- 18.38 % for respondents who believe that they can use tools related to AI well;
- 17.47 % for respondents who enjoy education in the field of AI;
- 17.30 % for respondents who agree that knowledge of AI will give them an advantage in their future career;
- 17.05 % for the respondents who think that knowledge of AI will help them find a good job in the future.

Transferring own data

Secondly, transferring one's own data is explored.

To be reluctant to transfer one's own data to a provider that uses more energy-efficient and water-cooled data centres is a characteristic with odds higher by:

- 25.29 % for respondents who think that understanding AI will contribute to their future profession;
- 25.12 % for respondents who believe that they will learn to understand the fundamental AI concepts;
- 24.52 % for respondents who agree with the usefulness of learning about AI in personal life, study and work;
- 24.32 % for respondents who think that self-education in the field of AI enriches their life;
- 23.88 % for respondents who agree that knowledge of AI will give them an advantage in their future career;
- 23.57 % for respondents who will try to keep up with the latest technologies in the field of AI;
- 23.50 % for respondents who enjoy education in the field of AI;
- 22.55 % for respondents who learn effectively while completing tasks;
- 21.79 % for respondents who usually ask classmates, colleagues or friends for help when they run into a problem in the activities related to AI;
- 21.69 % for respondents who know what AI is and remember its definitions;
- 19.06 % for respondents who can solve problems through AI (for instance, chatbots, robotics);
- 18.05 % for respondents who can evaluate applications and concepts of AI for different situations, who would be more reluctant to achieve good results in AI tests.

Leaving a favourite social network

Thirdly, leaving a favourite social network is examined.

To be reluctant to leave a favourite social network that does not use energy-efficient and water-saving opportunities in its data centres is a characteristic with odds higher by:

- 24.33 % for respondents who often look for other materials about AI, such as books or magazines, in their own free time;
- 23.81 % for respondents who often discuss AI with classmates, colleagues or friends in their free time;
- 21.99 % for respondents who actively participate in educational activities focused on AI;
- 15.53 % for respondents who can create a machine-learning model to solve problems;
- 14.41 % for respondents who can compare different concepts of AI (for instance, deep learning, machine learning);
- 14.40 % for respondents who believe they will use skills in the field of problem-solving using AI in their work;
- 13.16 % for respondents who know some of the fundamental principles of how AI works (for instance, linear model, decision tree, machine learning);
- 12.74 % for respondents interested in discovering new AI technologies;
- 12.44 % for respondents who are sure that will achieve good results in AI tests, who would be more reluctant to achieve good results in AI tests;
- 11.81 % for respondents who think that knowledge of AI will help them to find a good job in the future;
- 11.68 % for respondents who think that understanding AI will contribute to their future profession;
- 11.62 % for respondents who agree with the usefulness of learning about AI in personal life, study and work.

Stopping the use of a favourite streaming platform

Fourthly, stopping the use of a favourite streaming platform is scrutinised.

To be reluctant to stop using a favourite streaming platform that does not use energy-efficient and water-saving opportunities in its data centres is a characteristic with odds higher by:

- 17.57 % for respondents who often look for other materials about AI, such as books or magazines, in their own free time;
- 16.41 % for respondents who usually ask classmates, colleagues or friends for help when they run into a problem in the activities related to AI;
- 14.94 % for respondents who can create a machine-learning model to solve problems;
- 14.93 % for respondents who agree with the usefulness of learning about AI in personal life, study and work;
- 14.92 % for respondents who actively participate in educational activities focused on AI;
- 12.51 % for respondents who think that knowledge of AI will help them to find a good job in the future;
- 12.28 % for respondents who can compare different concepts of AI (for instance, deep learning, machine learning);
- 12.10 % for respondents who think that understanding AI will contribute to their future profession;
- 11.94 % for respondents who think that their future career will include AI;
- 11.85 % for respondents who know what AI is and remember its definitions;

– 10.67 % for respondents who think that self-education in the field of AI enriches their life;
– 10.06 % for respondents who are sure that will achieve good results in AI tests, who would be more reluctant to achieve good results in AI tests.

Stopping the use of a favourite GenAI platform

Fifth, stopping the use of a favourite GenAI platform is scrutinised.

To be reluctant to stop using a favourite GenAI platform that does not use energy-efficient and water-saving opportunities in its data centres is a characteristic with odds higher by:

– 22.05 % for respondents passionate about studying materials about AI;
– 16.65 % for respondents who agree with the usefulness of learning about AI in personal life, study and work;
– 14.45 % for respondents who know what AI is and remember its definitions;
– 14.36 % for respondents who usually ask classmates, colleagues or friends for help when they run into a problem in the activities related to AI;
– 11.67 % for respondents who often try to explain the teaching material about AI to their classmates;
– 11.45 % for respondents who think knowledge of AI will help them to find a good job in the future;
– 11.40 % for respondents who think that self-education in the field of AI enriches their life;
– 11.06 % for respondents who are interested in discovering new AI technologies;
– 10.24 % for respondents who believe that they will learn to understand the fundamental AI concepts;
– 10.14 % for respondents who understand how AI perceives the world (for instance, seeing, hearing) to solve various tasks;
– 9.94 % for respondents who believe they will use skills in the field of problem-solving using AI in their work;
– 8.51 % for respondents who can compare different concepts of AI (for instance, deep learning, machine learning).

Summary and critical comparative view

The quantitative expression of the individual statements within the examined dimensions does not have a comparative character or comparative goal, but its strong benefit lies in the construction character in the subsequent examination of the sensitivity of individual behavioural factors and aspects. For this reason, its strong methodological potential in the development of an AI literacy system with the implemented environmental components is evident. Hence, subsequent research and access to more deeply structured data are necessary. As the latest research studies have demonstrated, AI literacy and environmental literacy will be a rudimentary part of ensuring countries' environmental policy, which will face unusual demands as it will be driven by strong technological development.

The perception of energy consumption in relation to technological development requires the understanding of serious social interactions mediated by technologies. Piccolo et al. (2017) confirmed that environmental and energy issues have sociocultural characteristics, explaining the differentiated perception of energy intensity and sustainability in a relation to AI tools found within the Czech population. Piccolo et al. (2017) proposed using a socially inspired design approach when investigating energy awareness and changes in behaviour and willingness to change habits, forms and ways of using individual AI tools. Understanding the differences in personal motivation and learning confidence in relation to AI literacy and AI tools found in the research also points to the necessity of understanding the interpersonal dynamics between humans and AI because this is the only way to optimise their performance potential.

This fact was also highlighted by Mallick et al. (2024), who discussed the effects of emotional utility as well as that the integration of emotions within the AI community as having a positive impact on human perception and behaviour. This implies that emotions can be used as a tool to increase the acceptance rate of AI within the selected community and to improve the overall experience with AI. This can also have a strong positive impact on AI literacy tools adoption in various population structures. Similarly, Bewersdorff et al. (2024) confirmed that cognitive, effective, and behavioural variables related to AI build AI self-efficacy. AI use and positive attitudes towards AI can significantly predict interest in AI, and if this interest is supported by appropriate AI tools, its own effectiveness will increase. The research findings, supported by the outcomes of the research studies, create an appeal for the necessity of creating educational strategies that will focus not only on AI literacy but also on supporting population's attitudes, use and interests in AI and its tools to effectively promote AI self-efficacy. Great emphasis must be placed on designing inclusive AI educational programmes that will reflect the different needs, knowledge and experiences of the different minority population groups and thus eliminate the inaccessibility of AI within some communities (Robinson, 2020; Schiff, 2022). Obaideen et al. (2024) also defended the democratisation of access to AI technologies in marginalised regions and pointed to the need to use tools for a sustainable and fair future. The perception of the critical aspects of AI's environmental sustainability is related not only to the population's current AI literacy but also to its adaptability, critical thinking and analytical skills. Imjai et al. (2025) confirmed in their study that AI literacy has a significant positive impact on adaptability and critical thinking, with adaptability playing a crucial role in enhancing the actual use of AI knowledge.

When designing AI literacy systems, its holistic understanding must be used, taking into account the strongly interdisciplinary effort to measure AI literacy in a comprehensive way but also general and domain-specific AI literacy as well as AI ethics (Knoth et al., 2024). The development of AI literacy now goes beyond the cognitive aspects of conceptual knowledge as strong pressure advocates developing domain-specific AI literacy and competency dimensions of cognition, behaviour and attitudes. Future AI evaluation tools will feature both general and domain-specific aspects of AI literacy, including ethical AI literacy (Knoth et al., 2024).

Exploring respondents' attitudes across the numerous attributes listed in the data description section also creates a conceptual space for examining the factors of behavioural change that may be determined by increasing personal AI literacy. Nevertheless, real changes in respondents' attitudes are highly difficult to predict. As Alvi et al. (2024) also stated, the concern is that the population's orientation towards convenience – their promoted or desired lifestyle prioritising convenience over sustainability – may lead to increased resource consumption, raising challenges for sustainable consumption (Lubowiecki-Vikuk et al., 2021). This aspect may differ in relation to AI as well as in relation to saving food, water and energy. Managing energy demand and creating effective and adaptable energy strategies, which is reflected through technological development, is possible with active institutional support not only at the national but also at the international level. Francisco and Linnér (2023) pointed to the need for analyses that are rudimentary for policymaking and reports for the United Nations, European Union institutions, and World Economic Forum. Better data analysis and the acquisition of quantitative knowledge will allow countries to improve and enhance their energy management and thus achieve an optimal level of environmental sustainability at the projected pace of technological development in the world.

Limitations

This research study was based on data from primary research within the Czech population. The analytical processes were determined by the defined research questions, which did not include sociodemographic characteristics or geographical aspects. Their application could provide additional views on the perception of environmental issues across population groups, which could also explain some of the findings. Similarly, for the sake of the data-centre issue, a differentiated view of the different population groups depending on the influence of media, education and employment position could be obtained by extending the procedural framework of the study. Applying these classification aspects in the analysis could lead to obtaining additional interesting outcomes and thus to discovering new profiles of the population groups and their behaviour included in the different geographical structures. These facts confirm the need for deeper investigation of the examined issue and the implementation of multidimensional analyses in this field.

Conclusion

Although the potential of AI in achieving sustainable solutions to environmental issues is currently strongly proclaimed, the rapid development of GenAI and of its increasingly sophisticated forms will contribute to increasing energy consumption. Implementing green AI will become a great challenge for the population. For its successful adoption, systematically examining and to evaluating the population's perception and its attitudes towards the environmental challenges that green AI brings is necessary. Owing to the lack of transparency in resource consumption and the growing environmental threats associated with increasing energy consumption, the autonomy, transparency and environmental sustainability of AI may be at risk. The pressure of Chinese enterprises after the introduction of the GenAI platform DeepSeek changes the behaviour of the main players in this field. This will have a fundamental impact on the environmentalism and energy consumption of AI technologies.

This study aims to examine the relationships between the selected aspects of the use of GenAI systems and the environmental perception and behaviour of their users to understand the population's current environmental attitudes in relation to environmental risks and environmental sustainability. The more often people use GenAI systems, the more distant they consider the effects of climate change in time. The low frequency of use of ChatGPT may influence a higher willingness to change popular GenAI systems that are not maintained by environmentally friendly data centres. The frequency of ChatGPT use influences individuals' perception of the importance of climate-change solving. Respondents who use GenAI systems more frequently perceive climate change as less important. The low frequency of ChatGPT usage is associated with a lower willingness to change email provider, transfer own data, leave social networks, stop using a favourite streaming platform and stop using a favourite GenAI platform. The respondents' attitudes show a behavioural change. Internal personal motivation and self-confidence in learning, interest in career and self-confidence when using AI, behavioural aspects, and cognitive aspects are altered considerably. Regarding internal personal motivation and self-confidence in learning, changing email address is less possible when respondents are more confident in using AI tools. The possibility of transferring one's own data raises with awareness of AI among the respondents. Leaving a favourite social network is higher for the case of interest in career and self-confidence when using AI. Altogether, the behavioural aspects bring higher odds of doing all the explored actions, meaning that the behavioural perspective demonstrates higher shifts in the respondents' decision-making processes. The lowest increases of the odds of doing the discussed actions are found with regard to stopping the use of a favourite streaming platform and a favourite GenAI platform.

The outcomes of the study are beneficial for information strategy creators, for experts in the field of development and implementation of AI technologies, for creators of innovation and education strategies and for a large institutional platform. They also offer much valuable information for creators of monitoring and regulatory mechanisms at government levels as well as for experts in the field of behavioural and ethical sciences. The details of the examined aspects in a relation to behavioural and AI literacy aspects creates a unique platform for developing benchmarking indicators in this field and mechanisms to measure the relationships between individual levels of literacy and user experience, as well as targeted awareness of the energy demand and sustainability of AI technology's development.

Ethical approval

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

CRediT authorship contribution statement

Vaclav Moravec: Writing – review & editing, Writing – original draft, Validation, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Beata Gavurova:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Resources, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Viliam Kovac:** Writing – review & editing, Visualization, Software, Formal analysis, Data curation.

Conflict of interest

Vaclav Moravec declares he has no conflict of interest.
Beata Gavurova declares she has no conflict of interest.
Viliam Kovac declares he has no conflict of interest.

Data availability

Data will be made available on request.

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Supplementary materials

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