Towards Sustainable AI: Does Environmental Consciousness Impact AI Usage?

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Abstract

The development and use of AI affect the environment and resource use through the construction of data centres and the operation of AI models within them. To manage these impacts, user-centrically designed, environmentally responsible AI approaches need to be created to enhance users' agency in choosing the AI models for their needs. So far, the understanding of motivations for AI usage and the understanding of the role of environmental awareness in those decisions is limited. Besides, no empirical studies on public awareness of AI's environmental impact exist. Previous research on green consumption has studied how environmental awareness can lead users to consume greener alternatives. HCI research has contributed to quantifying the environmental footprint of AI systems and understanding the choice of certain AI products, but has so far not included on environmental awareness. To create user-centric, environmentally responsible AI approaches, it is necessary to understand what the motivations for AI use are and how novel AI applications can meet those needs. This work-in-progress paper outlines the related literature and methods for a survey to examine the association between environmental awareness and AI use intention. The planned survey will target a representative sample of the German population stratified by age, gender, and education. For the analysis of the data, a partial least squares structural equation modelling (PLS-SEM) will be used. We expect this survey to contribute to an understanding of the requirements for AI approaches centering around users needs' and not growth.

CCS Concepts

• **Human-centered computing → Human computer interaction (HCI)**.

Keywords

Sustainability, Sustainable AI, Environmentally Responsible AI, Green Consumption

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1 Introduction

The size of artificial intelligence (AI) models and their corresponding environmental impacts have grown substantially in recent years. The focus on achieving higher model accuracy through big-data approaches and increased computational power has led to higher resource costs for model training and inference in data centres [33]. This has an effect on the environment and resource usage through the construction of data centres and the operation of AI models in those data centres. Although data centre construction contributes about 30% to the emissions of an AI task [44], fine-tuning to new data and inference of models is also energy-intensive [38]. The development of large-scale AI models has hence contributed to climate change and ecological problems.

The use of AI can significantly influence overall environmental impact. Exact data on privately used AI applications is not publicly available [21]. Therefore, it is difficult to make precise assessments of the extent to which environmental impacts are attributable to individual use. The approximate estimates vary between 0.1 Wh and 1600 Wh for different queries and models for each use [24]. It has been shown that minor changes in the user behavior, for example using a task-specific model instead of a generative AI, can have a large influence on the environmental impact of AI [25]. Additionally, some tools have been developed to show the developer or consumer how the model choice influences the environmental impact [7, 32]. The potentially significant impact of users on AI's environmental footprint has been extensively studied, and tools to make this individual footprint transparent have been proposed. However, to the best of our knowledge, studies that incorporate users' perspectives on unsustainable AI use are rare.

Moving away from AI methods that focus solely on computational power growth should be linked to user-centric perspectives.

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So far, sustainable AI research has focused on improving the efficiency of models relying on big-data to minimise their environmental impact [33]. However, it has been shown that increased model efficiency does not necessarily lead to lower environmental impact, as it is often accompanied by increased demand [23, 39]. Therefore, not only is more efficiency of existing AI solutions required, but also novel methods beyond big-data approaches [31]. A post-growth philosophy can help identify alternative paths for AI development [35]. It shows how quality of life can be centred instead of growth in technological advances, and refocuses the goals of technology design. Aligning with this perspective, recent sustainable HCI (SHCI) research has centered around users' needs in sustainable design rather than treating them as a problem [12]. User-centric perspectives should be central when considering environmentally responsible AI alternatives, as it can support shifting the focus in sustainable AI away solely improving models applying big-data.

To develop such AI approaches, it is necessary to understand whether environmentally friendly approaches to AI can meet users' needs. As of now, no empirical evidence exists of the public's awareness of AI's environmental impact [18]. It has been studied, though, how environmental awareness can lead consumers to consume greener alternatives with other products [3, 27] and what influences the choice of using AI products [1, 4]. How the environmental impact of AI influences the decision to use AI has not been quantified. It has only been hypothesised that the impact is only known to a few people [30]. An understanding of the connection between AI usage behavior and the awareness of the environmental impact of AI is missing. A clearer understanding of how the individuals' awareness of the environmental costs influences the use of AI models is a step towards understanding user perspectives and needs of an environmentally responsible AI. This work-in-progress paper contributes to filling this research gap by reviewing green consumption literature on green behavioral intention and deriving a planned survey methods. The upcoming survey is intended to answer the following research question: How is the behavioral intention and attitude towards AI associated with environmental awareness?

The survey will target a representative sample of the German population, as Germany is a country with relatively high environmental awareness [43] and otherwise on average neutral opinion on AI's benefits and drawbacks [26]. It can therefore provide a first understanding of the correlation between environmental awareness and AI usage behavioral intention. This work-in-progress, therefore, provides initial insights for the SCHI community on how the role of environmental awareness in AI user behavior can be studied.

2 Related Work

The impact of environmental consciousness on user behavior in general has been studied in various contexts. Survey studies have shown how environmental consciousness and ecologically conscious behavior relate to effective green purchase behavior [3, 27], how attitudes and subjective norms are determinants for the acceptance of green products [9], and how subjective norms, environmental consciousness and perceived marketplace influence impact attitudes and green purchase intention [15]. Some scholars have built up on the theory of planned behavior (TPB) [9, 29], which is an updated version of the theory of reasoned action (TRA), to explain human behavior [2]. The theory assumes that behavior is a result of rational choice, which is influenced by attitudes, subject norms and perceived behavior control. It predicts that the probability of behaving a certain way increases, if a person has a positive attitude towards the expected behavior, has social support for behaving the expected way and has the ability to act in such a way [8]. A gap between attitudes and later behavior could be observed, showing that concern over environmental issues does not necessarily translate to green purchase behavior [45].

The green purchase behavior of technology has been observed regarding green alternatives, like energy efficient applications and e-vehicle use [16]. The influence of environmental impact of ICT-systems on consumption behavior has been studied by surveying the environmental awareness regarding ICT [46] and in specific about the cloud storage consumption [12]. The connection between environmental consciousness and AI-product use is underexplored.

Regarding AI, the sustainability of AI and the acceptance and use of AI has been studied. Some research has been done to quantify the environmental impacts of AI systems, for example the high energy consumption during training [25, 38] and inference [24, 44], and the water demand of AI models [21]. Recently, the public interest has risen, shown by an increase in online articles regarding the sustainability of AI [18]. The acceptance and use of AI have been studied, without including the sustainability of AI. Some studies have built up on the technological acceptance model (TAM) which provides a theoretical background for first acceptance of new technologies [10]. As an extension of the TAM, the unified theory of acceptance and use of technology (UTAUT) combines acceptance with later use [40]. This model was firstly designed to study individual technology acceptance in workplace settings. Expanding on that, the UTAUT 2 model includes dimensions for private use [41]. For AI products the individual consumption behavior has been studied, for example in the case of the use of AI chatbots by students [14, 19] and the acceptance of AI-supported shopping [28]. More broadly the intentions to use generative AI [1, 20], the influences on continued motivation to use AI [4] and the perception of AI [5, 11] have been studied. Hence, the literature so far has studied the impact of environmental consciousness on user behavior for diverse products, the environmental impact of AI and the AI use in specific contexts. A focus on the impact of environmental consciousness on AI-usage behavior remains missing.

3 Methodology

Measures. Deducted from TPB behavioral intention (BI) is influenced by three variables, the Attitude (ATT), the Subjective Norms (SN) and the Perceived Behavioral Control (PBC). Furthermore, Environmental Consciousness (EC) is integrated by several studies into the TPB to measure its influence on BI [29].

ATT represents the degree of favor for a specific behavior which is developed from believes [29]. The target behavior is evaluated based on the attitudes leading to a positive or negative influence on the behavioral intention in the context of green behavior [9, 15]. They create the expectation of a particular outcome, for example less impact on the environment.

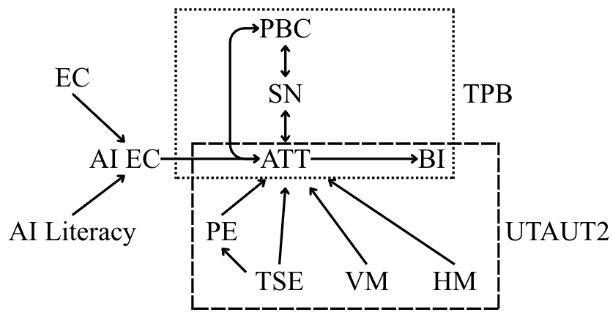

Figure 1: Proposed model with ATT and BI as dependent variables and EC, AI Literacy, PBC, SN, TSE, VM and HM as independent variables. Sociodemographic control variables are not included for model clarity.

SN refers to the judgment of the social environment, for example family and friends, and their perceived attitudes toward the planned behavior [9]. It is a form of social pressure to act a certain way due to the acceptable behavior within certain group[15]. They can have a strong influence on individual behavior, and can positively influence green behavioral intentions [29].

PBC measures the perceived ability to behave in the desired way, for example the perceived ease or difficulty to buy green products [15]. It also directly impacts the behavioral intentions and can be influenced by experiences [29].

EC does not occur in the original TPB, but is an integrated concept that has been used by green consumption scholars to study green behavioral intentions and green consumption behavior. It reflects the awareness of environmental impacts and the values and beliefs towards such impacts as the concerns and perceptions on environmental problems [9]. A possibility to reflect on one's own impacts on the environment and the recognition of the necessity for protection are included. It has been found that environmental consciousness leads to a more positive attitude and perceived behavioral control towards green products and is a precursor to pro-environmental behavior [37].

Three more measures from the UTAUT 2 applied by the research on technology acceptance and can be integrated, to specify the use of technology. ATT is influenced by Performance Expectancy (PE), Hedonic Motivation (HM), Value for Money (VM). As it is expected that AI Literacy has an influence on the awareness of AIs environmental impact, it is also integrated as a concept.

PE refers to the degree of expectation that applying the tool will enhance the performance of the user in a specific way or ease a certain task [1]. It indicates the perceived usefulness of the technology, and directly influences the attitudes towards the technology and the intention of use.
The Technology Self-Efficiency (TSE) is the perceived ease of use or degree of effort of a certain technology. It reflects the individual's belief in their own ability to use the technology effectively [1]. A high TSE can positively influence the usage of advanced features of the technology and therefore influences behavioral intentions, as well as PE.

HM was included by the UTAUT 2 and indicates the fun or pleasure derived from using the technology [41]. A high expected HM can result in positive attitudes towards the application and an increased intention of use. VM refers to the price the users need to pay for the technology and the perceived benefits of the technology. It is a trade-off between the cost for the product and the perceived outcome of using the technology [41].

AI Literacy refers to the skills regarding the use of AI and the knowledge of AI [42]. In contrast to other technologies that have been used for a longer time, or where the environmental impact is more tangible, AI is still an emerging technology. Therefore, it is expected that the literacy of AI correlates with the attitudes towards AI and the awareness of AIs environmental impact.

What correlation is expected between the variables is visualized in figure 1. Therefore, this study aims at answering the following research questions:

RQa) Does AI literacy correlate with environmental awareness and attitudes?
RQb) Do hedonic motivation, value for money, ease of use, perceived usefulness, and subjective norms correlate with the attitudes and behavioral intentions towards AI?
RQc) Does an association between environmental awareness of the impacts of AI and the behavioral intention towards AI products exist?

Design. The first section of the survey will include sociodemographic control measures for the demographics (age, gender, and education) of the participants. The second, third, and fourth will include questions regarding AI, respectively AI literacy [42], questions to understand what specific AI products are used and the questions stemming from UTAUT 2 measuring the intention for AI use [41]. The last block will be designed to measure concepts regarding environmental consciousness and include questions for the measures derived from the TPB to understand other possible influences on BI [29]. The assessment will be done by using a 5-point likert scale for each block.

Sample. In the data collection a representative sample of German population over the age of 18 will be gathered. Germany has been chosen as a case study, as the environmental consciousness is relatively high [43] and opinions about AI tend to be relatively neutral [26], suggesting that no strong biases for or against AI will influence the survey otherwise. To test the questionnaire a pilot study with university students will be conducted in April 2026 and the questionnaire will be refined accordingly. The representative sample size for Germany will be calculated with the appropriate measures, and the data collection will be done in May 2026.

Analysis Plan. For the analysis of the data a partial least squares structural equation modelling (PLS-SEM) will be applied, as this is widely used to estimate complex relationships.

4 Contribution to HCI

This work-in-progress contributes to the inclusion of sustainability into HCI research. Influenced by HCI's own contribution to climate change through working with generative AI models and other environmentally unfriendly technologies [17] a desire for climate-conscious and inclusive HCI has emerged in the last decades [34]. Through sustainable HCI (SHCI), which includes perspectives from psychology, ecology and climate science, the focus of HCI research is aligned with the goal of enhancing sustainability [22, 34]. By focusing on AIs ecological drawbacks, this work aligns with the objectives of SHCI. Furthermore, the literature used in this work broadens SHCIs' interdisciplinarity by incorporating green consumption. Therefore, this work contributes to HCI by focusing on sustainability and including further interdisciplinary literature.

Through taking a user-centric approach, this work-in-progress contributes to questioning growth assumptions in HCI. Research questioning HCIs' connection to economic growth has increased, and it was found that growth assumptions are deeply embedded in the discipline itself [36]. One proposed solution to the environmental problems accompanying this growth from HCI is tools reporting the individual contribution [7, 32]. These tools often lack the inclusion of stakeholders and users [13]. Further, it has been argued that the focus should not lie on persuading users, but on creating alternatives beyond growth [6]. The planned survey is in line with the arguments for alternative technologies centring around users' needs instead of economic growth. It could, however, yield the result that environmental awareness does not correlate with AI usage. This would indicate that users needs' in Germany currently align with growth objectives. The result would still be of value to SHCI, as it would strengthen the need to include people who are affected more heavily by AI's environmental impact, like people living around AI data centres. Outlining a method to understand the impact of environmental awareness on AI use can support the research on user-centric and environmentally responsible AI methods, and therefore contributes to an overarching goal of SHCI to include sustainable post-growth objectives.

5 Conclusion

As the demand for AI and its associated environmental impact continues to rise, user-centric approaches for environmentally responsible AI remain limited. Furthermore, there exists no empirical evidence of public's awareness of AIs environmental impact and the understanding of motivations for AI so far do not incorporate environmental awareness. To fill this research gap, this work-in-progress paper presents the literature and method to survey AI users. The survey will further provide insights into AI literacy and motivation for AI use, and we expect initial insights in relation to the awareness of AI systems environmental impacts. These findings could provide potential pathways for the HCI-community towards building user-centered green AI approaches from a post-growth perspective. Future research can expand on this work and study reasoning for using AI in more depth. This could be done through qualitative methods to understand the users requirements for a post-growth AI. Furthermore, the perspectives included in this study are very narrow, people most affected by unsustainable AI have not been included and should be considered.

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