Human-AI Collaboration for Environmental Sustainability - Use Cases, Impacts, and Modes of Augmentation

Yao Zhang, Alexander Richter and Yvonne Hong

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Full research paper

Yao Zhang
School of Information Management
Victoria University of Wellington
Wellington, New Zealand
Email: y.zhang@vuw.ac.nz

Alexander Richter
School of Information Management
Victoria University of Wellington
Wellington, New Zealand
Email: alex.richter@vuw.ac.nz

Yvonne Hong
School of Information Management
Victoria University of Wellington
Wellington, New Zealand
Email: yvonne.hong@vuw.ac.nz

Abstract

The world is currently facing a range of environmental challenges, including climate change, resource depletion, and biodiversity loss. Human-AI collaboration (HAIC) offers new momentum for addressing these issues. However, there is no comprehensive understanding of how HAIC can impact environmental sustainability. We conducted a systematic literature review on HAIC for Environmental Sustainability (ES). After analyzing 35 relevant articles, we identified 19 HAIC use cases for ES, such as smart sustainable mobility, route planning, and species identification. The use cases show the potential of HAIC to positively impact ES. For instance, HAIC contributes to energy conservation, waste and pollution reduction, and biodiversity preservation. In addition, we identified three main modes of augmentation in HAIC for ES: decision support, interaction and adaptation, and engagement and communication. Based on our review findings, we outline a research agenda, highlighting gaps such as the lack of studies contemplating the organizational level of HAIC.

Keywords: Human-AI collaboration (HAIC), Environmental sustainability (ES), Sustainability, Systematic literature review (SLR), Information systems (IS).

1 Introduction

The Earth's environment is facing severe challenges, including climate change, biodiversity loss, and resource depletion posing severe threats to ecosystems and humanity. The urgency of addressing environmental issues has never been greater (Leahy 2019). As we advance into the digital age, Artificial Intelligence (AI) is increasingly recognized as one of the most promising tools for promoting environmental sustainability (Duan et al. 2019). While concerns exist about AI's potential to increase energy consumption and carbon emissions, its true value lies at a higher level—how it can promote environmental sustainability (ES). AI has demonstrated substantial environmental benefits by enhancing data analysis, improving monitoring capabilities, and providing accurate predictions across various ES domains (Konya and Nematzadeh 2024). For instance, AI can optimize water resource management, monitor air quality, and predict energy consumption patterns to aid conservation efforts (Chen et al. 2021; De Vito et al. 2020; Xiang et al. 2021).

Several literature reviews have already summarized the applications of AI in environmental sustainability and offered suggestions for future development (Kar et al. 2022; Liengpunsakul 2021; Nishant et al. 2020; Schoormann et al. 2023). However, despite these advancements, the potential of AI cannot be fully realized without effective Human-AI Collaboration (HAIC) (Raftopoulos and Hamari 2023) . The foundation of HAIC lies in the complementary nature of human and AI strengths. AI offers three major advantages: first, it can automate repetitive and time-consuming tasks; second, it can process and analyze vast amounts of unstructured data; and third, it can integrate network resources to solve the most complex problems (Nishant et al. 2020). However, in some areas, fully removing human autonomy may not be desirable, particularly from a societal perspective, especially when addressing sustainability issues. In these situations, humans bring to the table strengths that AI lacks, such as intuition, creativity, and common sense (Hemmer et al. 2024). HAIC leverages the complementary strengths of human intelligence and artificial intelligence, enabling teams to achieve more collectively than either could accomplish independently (Dellermann et al. 2019). In this context, AI is used to augment human capabilities rather than replace them (Mandvikar and Dave 2023).

Although many studies have designed HAIC systems or frameworks from a technical perspective to achieve specific environmental goals (Bennitt 2024; Loske and Klumpp 2021), we lack a comprehensive overview of existing research. Therefore, this paper aims to address the following questions: 1. In what domains can HAIC contribute to ES? (i.e., what are HAIC use cases?), 2. What are the impacts of HAIC on ES? 3. How can AI augment humans to improve ES?

Addressing the three research questions, we provide a comprehensive overview of the state of the art of HAIC for ES enabling the identification of future research needs to explore how humans and AI work together to improve ES (Nishant et al. 2020; Taghikhah et al. 2022). We suggest a framework outlining 19 use cases of HAIC for ES, 9 impacts of these various use cases and 3 main modes of augmentation in HAIC for ES. Additionally, we propose a research agenda that addresses gaps in current knowledge, particularly in underexplored areas such as raw materials management and pollutant treatment. Furthermore, the study offers theoretical insights by integrating and extending existing research, while also calling for the development of a unified evaluation framework to assess the effectiveness of HAIC systems. These contributions advance academic understanding and provide practical guidance for implementing more effective HAIC practices in environmental sustainability initiatives.

The remainder of this paper is organized as follows. Section 2 presents the background of this study. Section 3 outlines the research methodology employed. Section 4 details the findings of the investigation. Section 5 discusses the findings, analyses the potential implications, and proposes a research agenda. Section 6 concludes the paper and discusses its limitations.

2 Background

Since 1987, when the World Commission on Environment and Development (WCED) introduced the concept of sustainability, efforts have focused on addressing environmental, social, and economic challenges. Defined as "development that meets the needs of the present without compromising future generations' ability to meet their own needs" (WCED 1987), sustainability emphasizes the widely accepted triple bottom line, which integrates the interdependent pillars of environment, society, and economy (Elkington and Rowlands 1999). In the intersection of AI and sustainability, there are two easily confused terms: sustainability of AI, and AI for sustainability. Sustainability of AI refers to the use of sustainable data sources, algorithms, and hardware to reduce carbon footprints and energy consumption (Van Wynsberghe 2021).

Research indicates that training AI models can lead to significant energy consumption and carbon emissions, with variations across different algorithms and hardware (Strubell et al. 2020). Therefore, developers should focus on creating more efficient and sustainable AI algorithms to enhance the sustainability of AI. AI for sustainability refers to the application of AI technologies to address environmental, social, and economic issues, thereby promoting sustainable development (Van Wynsberghe 2021). For instance, AI can be applied in water resource management to predict and optimize water conservation efforts (Nishant et al. 2020). In smart manufacturing, AI can enhance productivity, reduce energy consumption, and improve worker well-being (Choudhury et al. 2022).

HAIC refers to the process in which humans and AI systems actively collaborate, continually interact, and adapt to achieve a common goal (Lai et al. 2021). The essence of HAIC lies in leveraging the strengths of both humans and AI to achieve more than either could alone. HAIC has been successfully applied across economic, social, and environmental dimensions. Economically, HAIC is primarily focused on enhancing productivity (Sowa et al. 2021), increasing efficiency (Zhang et al. 2022), and reducing costs (Wang and Huang 2023). Additionally, HAIC can improve the quality of customer service by integrating human emotional perception with AI's processing efficiency (Qin et al. 2022). Socially, HAIC is widely applied in healthcare (Lai et al. 2021), education (Molenaar 2022), and the enhancement of worker well-being (Sowa et al. 2021). Environmentally, HAIC has extensively engaged in areas such as smart grids (Fan et al. 2024) and sustainable manufacturing (Meng et al. 2022).

Environmental sustainability is a crucial dimension of overall sustainability (Morelli 2011; Nishant et al. 2020). This encompasses various topics, including low-impact transportation, conservation of environmental assets (biodiversity, water resources, energy use, renewable energy, raw materials such as food and minerals, land-use sustainability), sustainable agriculture, and management of waste and pollution (waste reduction, recycling, reuse, repair, using environmentally responsible material, pollution monitoring, pollutant treatment). As the Earth's environment continues to deteriorate, there is growing concern about environmental sustainability (Nishant et al. 2020). Although HAIC has been practiced across various ES topics, how HAIC impacts ES remains unclear. Therefore, this study aims to identify different HAIC use cases for ES, discuss its impacts and modes of augmentation.

3 Methodology

This paper conducts a systematic literature review (SLR) of studies related to HAIC for ES. We followed the protocol by Kitchenham (Kitchenham 2004). The major advantage of SLR is that it provide information about the effects of phenomenon across various contexts and empirical methods (Kitchenham 2004), which is highly relevant to this study. Additionally, compared to traditional narrative reviews, it helps reduce bias (Tranfield et al. 2003). The aim of this research is to offer a comprehensive and impartial understanding of HAIC for ES through the integration and analysis of existing literature (Shahzadi et al. 2024). The first author independently analyzed and synthesized the results while adhering to SLR standards to maintain objectivity. After discussions and adjustments with the second author, the third author reviewed the results to minimize bias.

We selected the Web of Science (WOS) database for our search due to its rigorous and objective filtering criteria, which ensure the reliability of the studies it includes (Merigó and Yang 2017). Additionally, AI began gaining prominence around 2010, as noted by Digital Trends (Digital Trends 2019), making this an appropriate starting point for our search. To ensure comprehensive coverage, we combined a Systematic Literature Search with hermeneutic research, an interpretative and iterative approach that identifies relevant works (Boell and Cecez-Kecmanovic 2014; Nuswantoro et al. 2023). Unlike a linear search process, the hermeneutic literature review allows researchers to read, analyze, and revisit sources in cycles, deepening the understanding of complex and ambiguous topics over time (Boell and Cecez-Kecmanovic 2014). Additionally, HAIC is a relatively new term, with various studies discussing it under different terminologies (Memmert and Bittner 2022; Raftopoulos and Hamari 2023). Solely relying on specific search terms may result in missing relevant literature, as many articles do not directly use the term. A hermeneutic literature review mitigates this issue by allowing broader interpretations of the literature (Boell and Cecez-Kecmanovic 2014).

3.1 Systematic Literature Search

Due to the evolving terminology of HAIC, we included various labels such as hybrid intelligence, augmented intelligence, and human-AI teams, as these are often used synonymously under the broader definition of HAIC (Memmert and Bittner 2022; Raftopoulos and Hamari 2023). In terms of ES, we adopted Nishant's definition of the ES topics(Nishant et al. 2020). Finally, we employed inclusive search terms: ("hybrid intelligence" OR "Augmented Intelligence" OR ("human" AND ("AI" OR "artificial intelligence") AND ("team*" OR "collaboration"))) AND ("sustainable" OR "sustainability" OR "environmental" OR "ecological" OR "air" OR "water" OR "energy" OR "climate" OR "transportation" OR "agriculture" OR "biodiversity" OR "pollution" OR "recycle" OR "waste" OR "pro-environment").

3.2 Selection

We limited our search to articles, conference proceedings, and books. A keyword search in the WOS database identified 1,200 papers downloaded into an Excel sheet for further analysis. The papers were selected based on the following inclusion criteria: (1) focus on the collaboration between humans and AI, (2) focus on ES topics, and (3) written in English. The exclusion criteria were: (1) only focus on AI applications instead of collaboration with humans, (2) not focus on ES topics, (3) not written in English, (4) full text not accessible, and (5) low-quality research (i.e., non-peer reviewed articles).

The initial screening involved reviewing the titles and abstracts of the papers against the inclusion criteria, leading to the exclusion of 864 papers. The remaining papers were then read in full and re-reviewed based on the criteria, resulting in the exclusion of 315 papers. Ultimately, 21 papers were identified as relevant. These 21 papers were then included in a hermeneutic review search. By reviewing 21 articles, we gained a deeper understanding of the research questions, which led to the identification of additional search terms and multiple iterations of the search process. Additionally, we employed a snowballing strategy, which works by identifying other relevant articles that are cited within the previously reviewed papers (Boell and Cecez-Kecmanovic 2014). Through an iterative process and contextual understanding, we identified an additional 14 relevant articles. Thus, a total of 35 articles were included in the final analysis. The sample selection process is illustrated in Figure 1.

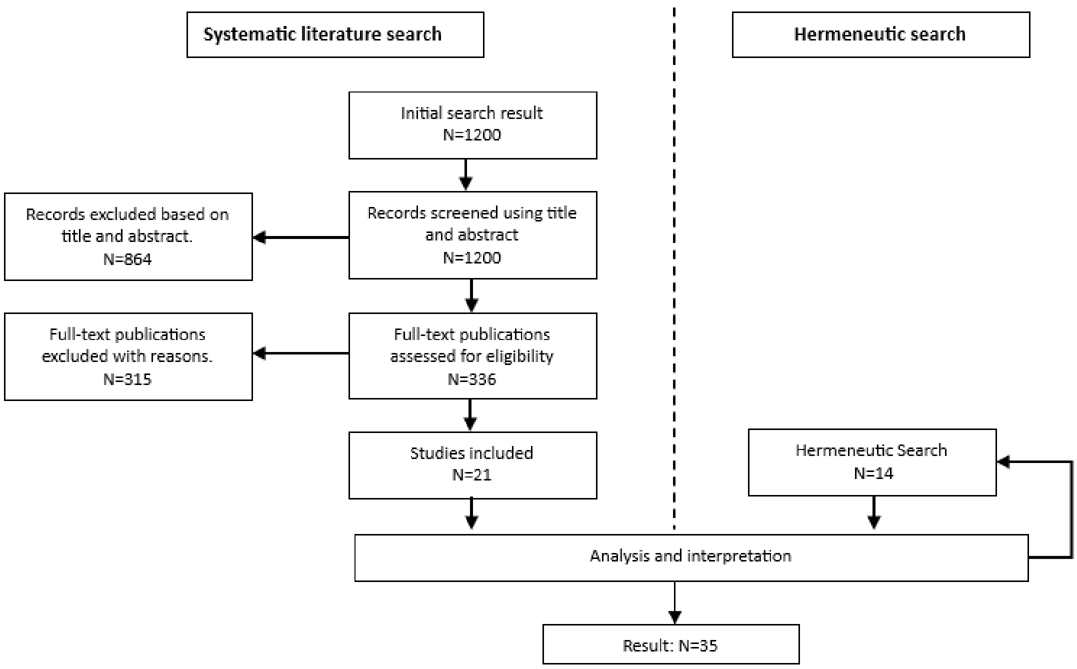

Figure 1. The Selection Process

3.3 Data Extraction and Analysis

The data extraction process aimed to identify key features in the selected articles to address the research questions (Okoli 2015). The basic information of the remaining 35 papers (publication year, authors, publication venue) was downloaded into an Excel sheet. After that, the first author developed an initial coding set based on the research questions, including HAIC use cases, impacts, and modes of argumentation, and manually coded all the papers. We applied thematic analysis to perform content analysis and used Nishant's definition of ES topics to categorize HAIC use cases. After the first round of coding, the authors reviewed and reflected on the results to assess their contribution to the research objectives and determine whether additional codes were necessary. Consequently, additional codes were generated to assess performance (research methods). The first author then re-coded the papers using the final code set, discussed the results with the second author, and the third author reviewed the results.

4 Findings

4.1 Identification and Bibliographic Data

We reviewed and analyzed 35 publications published between 2010 and 2024, including 9 conference papers and 26 journal articles. As shown in Figure 2, HAIC for ES is a relatively new topic, with the first related publication appearing in 2012. The literature from 2012 to 2020 primarily focused on the technical aspects of deep learning and its interaction and collaboration with humans. It wasn't until 2020 that the concept of HAIC in the context of ES was first introduced, gradually gaining attention from the academic community. Since then, the number of publications has steadily increased each year.

Of the reviewed literature, 21 papers were empirical, while 14 were non-empirical. The papers were classified as empirical and measured the performance of HAIC use cases in ES, demonstrating the effectiveness of HAIC. In contrast, the non-empirical papers either did not include performance evaluation or suggested it as an area for future work. The results indicate that most HAIC use cases for ES have confirmed the potential in this area. However, challenges remain in quantifying and measuring the performance of certain systems.

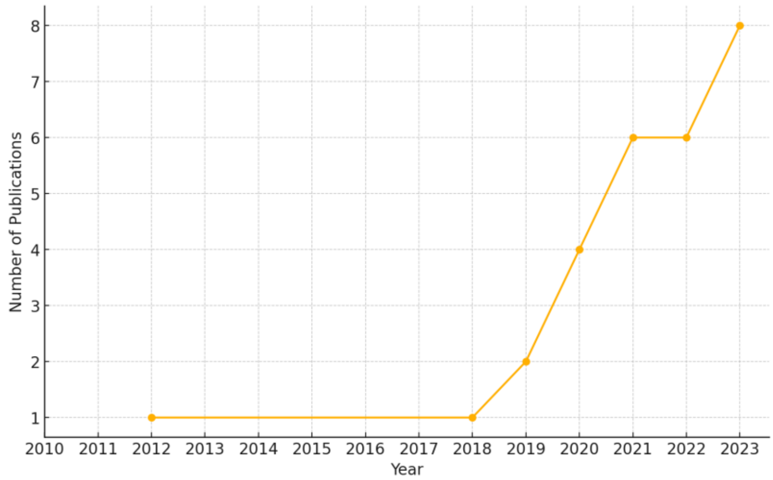

Figure 2. Publication year of papers

4.2 HAIC for ES: Use Cases and Their Impacts

To better understand how HAIC impacts ES, a summary of HAIC use cases within ES topics is provided as follows and illustrated in Table 1.

4.2.1 HAIC in low-impact transportation

Low-impact transportation aims to reduce the environmental impact of transportation by minimizing energy use and road transport pollution, as well as by introducing clean-fuel vehicles (Wismans et al. 2015). One important way to achieve low-impact transportation is through Smart Sustainable Mobility, which leverages information technology to optimize transportation systems, reducing congestion and emissions while meeting the diverse needs of users, thereby promoting sustainable development (Khamis and Malek 2023). This significantly reduces energy consumption and carbon emissions and decreases air pollution (Ketter et al. 2023). Moreover, efficient and safe route planning reduces congestion and vehicle energy consumption and significantly lowers emissions (Gajanand and Narendran 2013). By integrating human expertise with AI technology, HAIC can optimize route decisions in the face of complex and dynamic road conditions, further reducing carbon emissions and fully supporting the achievement of low-impact transportation.

4.2.2 HAIC in conservation of environmental assets

HAIC in biodiversity: Biodiversity refers to the variety of life forms on Earth, encompassing genetic, species, and ecosystem diversity, and includes diversity within and between (Jennings and Gaston 1996). Species identification, which involves classifying organisms based on their unique characteristics, provides crucial data for assessing and monitoring biodiversity (Balakrishnan 2005). This data is essential for implementing targeted conservation measures and effectively preserving biodiversity (Steele and Pires 2011). HAIC significantly expands the scope of sample collection by encouraging widespread citizen participation in the collection of species images. By integrating AI image recognition technology, HAIC can accurately map species migration corridors, thereby promoting biodiversity conservation.

HAIC in groundwater: Groundwater is a critical water resource globally, and its monitoring is essential for the timely detection and prevention of groundwater pollution (Madsen et al. 2007). Groundwater monitoring provides scientific evidence for water resource management, aiding in the development of effective conservation policies (Makanda et al. 2022). HAIC plays a vital role in this process by enabling AI systems to continuously learn from expert feedback, optimizing the planning and layout of monitoring wells, and improving monitoring efficiency and accuracy (Babbar-Sebens and Minsker 2012). This AI-based dynamic learning mechanism not only enhances the deployment of monitoring wells but also further promotes the effective protection of water resources.

HAIC in energy use: The process of energy utilization, which includes production, distribution, and consumption, is a critical aspect of energy management (Simion et al. 2023). In this process, HAIC has found widespread application in smart grids. In smart grids, AI can assist with decision-making by providing real-time monitoring and data analysis. Humans interact and collaborate with AI systems and grid control systems through visual interfaces, playing a critical role in complex reasoning and decision-making, especially in uncertain or emergency situations. Through this process, HAIC can significantly enhance decision-making quality in smart grids, leading to more efficient energy production, distribution, and transmission, thereby reducing energy waste and improving energy utilization efficiency (Fan et al. 2024; Pedretti et al. 2021; Stecyk and Miciuła 2023). In the energy distribution phase, HAIC plays a key role in Energy Building Optimization and energy operation by optimizing the energy distribution process, further enhancing energy efficiency and minimizing unnecessary energy waste (Alsamhi et al. 2024; Yang et al. 2022). Moreover, HAIC also contributes to the sustainability of AI technology itself by selecting more sustainable machine learning methods, which reduce the energy consumption of AI systems (CHAABEN 2023).

HAIC in renewable energy: Renewable energy refers to energy derived from natural processes that are replenished continuously under sustainable use, such as solar and wind energy (Arman and Yuksel 2013). The development of renewable energy helps reduce dependence on fossil fuels, thereby mitigating climate change and lowering carbon emissions (Arman and Yuksel 2013). However, developing renewable energy requires significant investment in infrastructure. The integration of HAIC and Cyber-Physical-Social Systems (CPSS) can support the effective incorporation of renewable energy into existing energy infrastructures, optimizing renewable energy utilization and reducing carbon emissions (Alsamhi et al. 2024). In renewable energy systems, AI uses image processing technologies to monitor equipment for potential faults and provides diagnostic recommendations. Human operators, leveraging their professional expertise, conduct on-site inspections and make final fault judgments based on AI's suggestions. This collaboration between AI and human expertise enhances the accuracy and efficiency of fault detection and maintenance processes in renewable energy systems. By detecting potential equipment failures in advance, HAIC can effectively reduce unplanned downtime, lower operational and maintenance costs, and minimize waste of renewable energy resources (Shin et al. 2021).

HAIC in land-use sustainability: Sustainable land-use refers to the balanced allocation of environmental resources to meet current and future needs (Kruseman et al. 1996). Reasonable planning, development, and protection of land resources under specific spatial and temporal conditions are crucial for achieving land sustainability (Han et al. 2023). A land planning design study in Seoul, South Korea, found that AI-assisted design can better integrate different human planning approaches into land-use decisions, thereby improving energy efficiency and land utilization rates, and promoting land conservation (Quan et al. 2019).

4.2.3 HAIC in sustainable agriculture

Sustainable agriculture refers to the enhancement of agricultural productivity without causing adverse effects on the environment and ecosystems (Pretty 2008). Improving agricultural sustainability can reduce the consumption of natural resources, protect biodiversity, and maintain the health of soil and water resources (Tilman et al. 2002). HAIC leverages the targeted integration of human intelligence and AI computational systems to optimize crop planning decisions, effectively balancing biodiversity and productivity (Berger et al. 2024). Additionally, by relying on farmers' experience, HAIC contributes to the effective preservation of soil health (Schöning and Richter 2021).

4.2.4 HAIC in management of waste and pollution

HAIC in waste reduction: Rapid urbanization, population growth, and economic development have accelerated waste generation, leading to pollution and waste management challenges, necessitating new strategies for waste management (Fang et al. 2023). Zhou et al. (2020) designed an intelligent waste management system that combines human strategic planning with AI's real-time monitoring capabilities to optimize waste disposal processes, achieve controlled operations, and enhance waste treatment efficiency (Zhou et al. 2020). Additionally, HAIC enhances human waste-sorting capabilities through AI, improving the accuracy of waste classification. Moreover, the interaction and engagement between humans and AI further increase public participation (Jacobsen et al. 2020)

HAIC in recycling: In manufacturing, disassembly is considered a critical prerequisite and bottleneck for promoting recycling (Sassanelli et al. 2021). Several studies have integrated HAIC into smart disassembly to facilitate recycling. First, AI can detect disassembled parts using algorithms to assess their condition and prepare them for further processing. Second, AI plans disassembly paths through algorithms and assigns tasks to either humans or collaborative robots based on task complexity. Finally, AI dynamically adjusts the task sequence through real-time feedback from sensors and hands over control to humans when emergency situations arise. For example, Meng et al. (2022) reviewed the intelligent disassembly of electric vehicle batteries and found that integrating human intelligence into AI-driven smart disassembly can improve safety, adaptability, and disassembly efficiency (Meng et al. 2022). Other studies have shown that HAIC in the disassembly of waste parts can optimize task allocation, provide personalized disassembly, and reduce disassembly costs(Amirnia and Keivanpour 2024; Jin et al. 2022).

HAIC in reuse: The circular economy aims to maximize the reuse of materials and components (Ghisellini et al. 2018). By extending the life cycle of materials and components, it reduces resource consumption and lowers energy use during production and waste treatment (Minunno et al. 2020). In the context of Industry 5.0, humans are integrated into intelligent processes, actively participating in the lifecycle assessment of products. AI, through the use of sensors and algorithms, dynamically provides real-time information on the product's health, energy consumption, and carbon footprint throughout its lifecycle. This helps humans make informed decisions on product maintenance, recycling, and material reuse, enhancing sustainability efforts and resource efficiency (Turner et al. 2022).

HAIC in using environmentally responsible material: Environmentally responsible materials are those that have minimal negative environmental impact. Using such materials can reduce environmental pollution (Ljungberg 2005). A case study in artisanal industries found that HAIC can improve the quality of decision-making, enabling artisanal economies to choose more sustainable materials and resources (Eglash et al. 2020). Additionally, IBM designed a human-AI co-creation platform that accelerates the discovery of substitutes for toxic materials through multiple interactions and iterations between AI and humans (Jansen and Segura 2023).

HAIC in pollution monitoring: Pollution monitoring provides real-time insights into pollution levels and trends, allowing for timely interventions to mitigate environmental harm (Artiola and Brusseau 2019). Research by Myeong and Shahzad demonstrated that incorporating citizen intelligence and public participation into air monitoring systems can significantly enhance the efficiency of air pollution management (Myeong and Shahzad 2021).

4.2.5 HAIC in environmental education

In addition to its practices in ES topics, HAIC also holds significant potential in the intersection of environmental and social dimensions, primarily in environmental education. Environmental education is a crucial means of promoting sustainability, as it is closely connected to everyone in society (Boca and Saraçlı 2019). However, the biggest challenge in environmental education is encouraging people to adopt a sustainable lifestyle (Zsóka et al. 2013). On one hand, HAIC can enhance human environmental knowledge and promote participation in environmental activities through AI-human co-creation and interaction. On the other hand, HAIC can provide more personalized environmental recommendations through human interaction and adaptation, thereby encouraging pro-environmental behaviours (Puerta-Beldarrain et al. 2023; Sanchez et al. 2022).

4.3 Modes of augmentation

We have found that 19 HAIC use cases across various ES topics have generated a range of positive impacts on ES. Additionally, in the context of ES practices, after analyzing these 19 use cases, we have synthesized three main modes in which AI augments humans to promote ES: decision support, interaction and adaptation, and engagement and communication.

ES Topics	ES HAIC Subtopics	HAIC Use cases	References
HAIC in low-impact transportation	Low-impact transportation	Smart Sustainable Mobility	(Ketter et al., 2023)
		Route planning	(Loske & Klumpp, 2021a, 2021c)
HAIC in conservation of environmental assets	Biodiversity	Species identification	(Bennitt, 2024; Picek et al., 2022)
	Water resources	Groundwater monitoring	(Babbar-Sebens & Minsker, 2012)
	Energy use	Smart Grids	(Alsamhi et al., 2024; Fan et al., 2024; Pedretti et al., 2021; Stecyk & Miciuła, 2023; Zhang et al., 2018)
		Energy Operation & Building Optimization	(Alsamhi et al., 2024) (Yang et al., 2022) (CHAABEN, 2023)
	Renewable energy	Renewable Energy production	(Alsamhi et al., 2024)
		Predictive maintenance	(Shin et al., 2021)
	Land-use sustainability	Land planning	(W. Chen et al., 2020; Quan et al., 2019)
HAIC in sustainable agriculture	Sustainable agriculture	Crop planning	(Berger et al., 2024; Schöning & Richter, 2021)
HAIC in management of waste and pollution	Waste reduction	Waste Treatment	(Jacobsen et al., 2020; Zhou et al., 2020)
		Process Optimization	(Alsamhi et al., 2024)
	Recycling	Disassembly	(Amirnia & Keivanpour, 2024; Jin et al., 2022; Liu et al., 2019; Meng et al., 2022; Qin et al., 2024; Wang et al., 2023)
	Reuse	Circular Economy	(Turner et al., 2022)
	Using environmentally responsible material	Environmental Material choosing	(Eglash et al., 2020)
		Replace toxic materials	(Jansen & Segura, 2023)
	Pollution monitoring	Air pollution management	(Myeong & Shahzad, 2021)
HAIC in Enviromental education	Environmental education	Public engagement	(V. Y. Chen et al., 2024; Lc, 2023; Rafner et al., 2023)
		Pro-environmental behaviour.	(Puerta-Beldarrain et al., 2023; Sanchez et al., 2022)

Table 1. HAIC use cases in ES topics

Decision support: HAIC can enhance the quality and performance of decision-making by integrating human strengths with AI capabilities, especially in complex and uncertain environments (Dolgikh and Mulesa 2021; Jain et al. 2022; Lin et al. 2024). In decision support, AI assists decision-making by analyzing vast amounts of data and performing complex computational tasks, offering recommendations or analyses. Humans, in turn, evaluate these AI-generated suggestions, integrating their professional expertise, experience, and ethical considerations to make the final decision. This collaborative approach significantly enhances efficiency in complex and dynamic environments and preserves human judgment. However, different individuals have varying perspectives on the role AI should play in decision support. Haesevoets' research indicates that in management decision, 5% of managers prefer AI to take a dominant role, 15% favor an equal partnership between humans and AI, 50% prefer humans to have the upper hand, and 30% prefer humans to have complete control over decisions (Haesevoets et al. 2021). When tasks are allocated appropriately, HAIC can outperform decisions made by either humans or AI alone (Fügener et al. 2021). However, improper task allocation in HAIC systems can lead to a loss of human trust, negatively affecting decision outcomes (Rastogi et al. 2022). Therefore, appropriate task allocation is crucial for effective decision support. Almost all HAIC use cases in ES emphasize the mode of decision support. For example, in smart grids, HAIC can optimize decision-making by combining AI's computational power with human logical reasoning, thereby improving energy efficiency (Fan et al. 2024).

Interaction and adaptation: The success of HAIC relies heavily on effective interaction and feedback between humans and AI, as well as adaptation based on that feedback (Fragiadakis et al. 2024). Interaction refers to the exchange of information between humans and AI during the collaboration process. This interaction can occur through natural language, graphical interfaces, or visualization tools, ensuring that AI understands human needs while allowing humans to interpret AI's outputs (Yang et al. 2019). Adaptability includes both AI learning from human decision processes and AI adjusting its behavior to positively influence collaborative performance (Zhao et al. 2022). Simultaneously, AI's adaptive capabilities encourage human partners to adjust their instructions, creating a bidirectional adaptation loop that enhances collaboration quality (Xu et al. 2011). This interactive and adaptive collaboration model enables more personalized decision-making and effectively boosts team performance while maintaining human trust in AI (Nikolaidis et al. 2017). In HAIC use cases for ES, system provides personalized services through interaction and adaptation, thereby improving team performance. For example, by integrating HAIC, intelligent transportation systems can adapt through interaction with humans to provide personalized low-carbon travel solutions, reducing energy consumption and carbon emissions (Ketter et al. 2023).

Engagement and communication: Collaborative engagement can make HAIC more effective (Puerta-Beldarrain et al. 2023). Especially in the context of environmental sustainability, achieving sustainability goals requires broad societal involvement, where human actions play a crucial role (Vlek and Steg 2007). In HAIC systems, allowing users to actively participate in the decision-making process fosters a sense of belonging, making them feel like a part of the system rather than passive recipients. This approach enhances user engagement and encourages more active participation in sustainability initiatives (Puerta-Beldarrain et al. 2023). Research shows that in co-creation systems, interaction between humans and AI enhances human engagement, leading to AI being perceived as a more reliable and intelligent partner (Rezwana and Maher 2022). In HAIC systems, interaction and communication with AI not only facilitate more effective task execution but also increase human engagement in the process (Jacobsen et al. 2020). In the context of ES, HAIC promotes human awareness of environmental issues and encourages active participation in environmental activities through AI-human interaction. For example, in citizen science, human take photos of species in different locations and upload them to platforms. AI then uses image recognition and data processing to map species migration corridors, which aids in planning protected areas. Through this process, human involvement increases their engagement in environmental conservation and raises environmental awareness (Chen et al. 2024).

5 Discussion

5.1 Implications of Findings

As environmental issues continue to worsen, there is an increasing need for innovative solutions to promote ES. HAIC presents new opportunities for improving ES. However, no systematic research has yet analyzed how humans and AI collaborate to impact ES. Through a systematic literature review of 35 articles, we found that HAIC for ES has gained significant attention since 2020, indicating a growing recognition of its potential in this area. Most studies empirically verify the effectiveness of HAIC in promoting ES. However, in certain contexts, some studies have proposed the challenges in evaluating performance. Additionally, we observed that most research focuses on the technical collaboration between humans and AI, with limited research exploring how humans and AI collaborate within organizational contexts to improve organizational ES. To address this, we identified 19 HAIC use cases in ES practices. By analyzing these use cases, such as, smart sustainable mobility, route planning, and species identification, we developed a comprehensive framework that facilitates a more holistic sociotechnical understanding of HAIC for ES (see Figure 3). The use cases have demonstrated a range of positive impacts on ES, such as reducing energy consumption and improving resource efficiency, which highlights the significant potential of HAIC in promoting ES. As a result, we should recognize the potential of AI in addressing environmental issues and engage in more ES practices. Additionally, we found that there is still some promising topics within ES domains that remain unexplored, such as raw materials, repair, and pollutant treatment. For example, some researchers have developed AI algorithms that, through computer vision and object recognition, identify raw materials in Waste Electrical and Electronic Equipment (Cabri et al. 2022). Future research needs to explore how these AI technologies can collaborate with humans to improve ES.

Lastly, through analyzing 19 HAIC use cases, we synthesized three main modes of augmentation to promote ES: decision support, interaction and adaptation, and engagement and communication. These three modes underpin successful HAIC for ES and provide insights for designing effective HAIC in the future. However, although we have identified these three main modes, their underlying mechanisms have not been thoroughly studied, which warrants further exploration in the future.

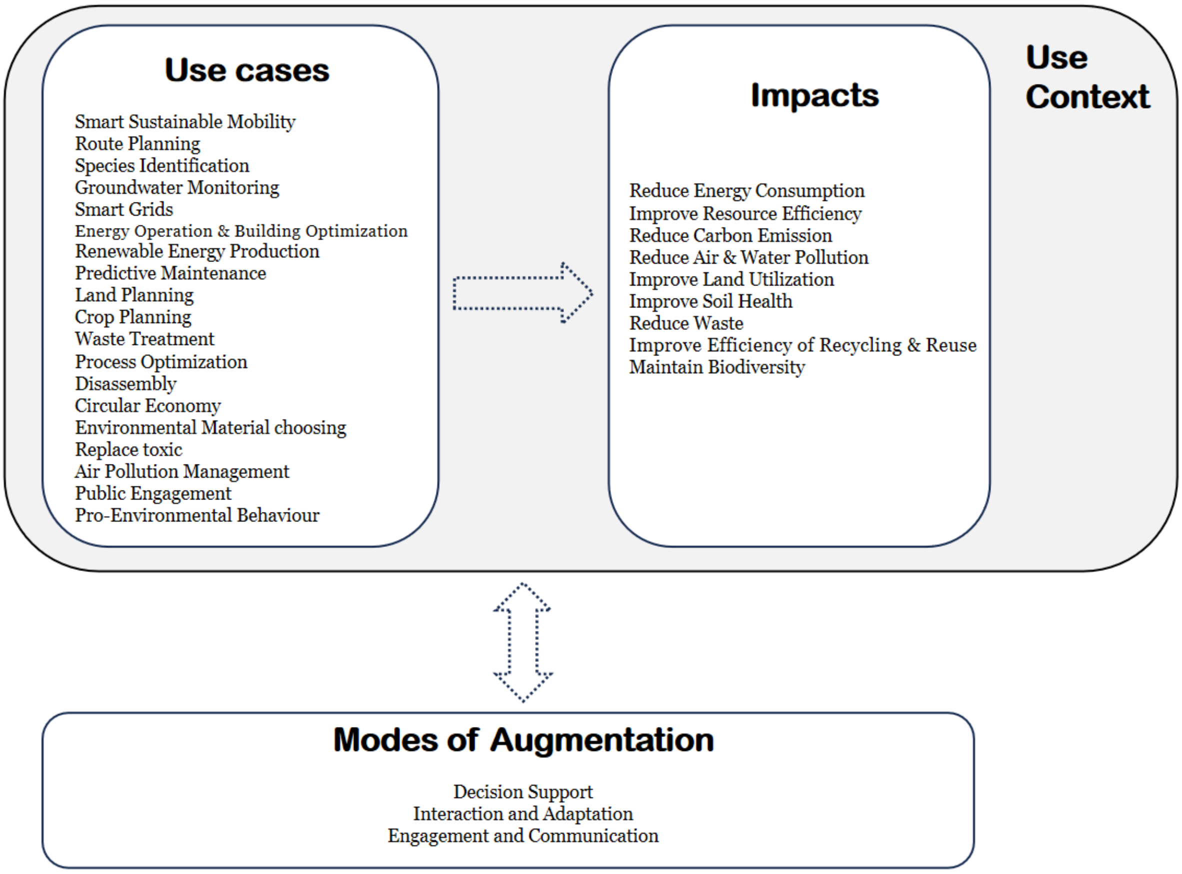

Figure 3. Framework for HAIC for ES

5.2 Research Agenda

Through the discussion of research findings, we identified the current state of research on HAIC for ES. Based on these findings, we have determined several key research questions to further the understanding and application of HAIC for ES.

How can HAIC be effectively applied to ES's underexplored areas?

While HAIC has shown promise in areas like smart grids and waste management, there remain significant gaps in topics such as raw materials management, repair optimization, and pollutant treatment. By combining human experience and ethical considerations with AI's capabilities, it is possible to significantly improve performance in these topics. Future research should explore HAIC use cases in these underdeveloped topics and improve existing use cases.

What are the mechanisms through which HAIC influences decision-making for ES?

Decision support is a critical dimension of HAIC. However, there is a need for deeper exploration into how HAIC improves decision-making processes in complex and uncertain environmental contexts. Researchers should investigate the specific ways in which HAIC can enhance the quality, efficiency, and outcomes of decisions in various ES scenarios.

How can HAIC systems be designed to foster better interaction and adaptation between humans and AI?

Effective interaction and mutual adaptation are key to successful HAIC. Future studies should focus on designing HAIC systems that encourage dynamic feedback loops between humans and AI, enabling both parties to adjust and optimize their contributions in real-time. Research should also examine how these interactions impact trust, efficiency, and overall system performance.

How can engagement and communication be improved in HAIC use cases to promote pro-environmental behaviours?

Engagement and communication are crucial for the success of HAIC in ES. Future research should explore strategies for enhancing human engagement with AI systems, particularly in ways that encourage sustainable behaviours. This could include investigating the role of personalized AI-driven recommendations and the impact of collaborative AI systems on public participation in environmental initiatives.

How can organizations effectively integrate HAIC into their sustainability strategies?

We found that nearly all HAIC use cases for ES are based on a technological perspective, focusing on the design of HAIC systems to achieve one or more environmental goals, such as improving resource efficiency and land use (see Table 1). However, current research lacks attention to the organizational level, which contrasts sharply with the academic focus on this topic. Future studies should examine how HAIC can be integrated into organizational sustainability strategies, considering factors such as leadership, culture, and the specific needs of different industries. Research should also investigate the impact of HAIC on organizational performance and its potential to drive systemic change.

What framework can be developed to evaluate the effectiveness of HAIC for ES?

We found that HAIC for ES still faces certain challenges in performance measurement. There is a need for a standardized framework to evaluate HAIC systems in the context of ES. Future research should aim to develop such a framework, allowing for consistent assessment of HAIC's impact across different environmental contexts and facilitating comparison of results across studies.

6 Conclusion and limitations

This study explores the impact of Human-AI Collaboration (HAIC) on Environmental Sustainability (ES) and its potential for driving meaningful change. Our comprehensive review highlights HAIC's effectiveness in areas such as energy conservation, waste reduction, and biodiversity preservation. To further advance the field and address ongoing challenges, we propose a research agenda that underscores the need for further investigation, particularly at the organizational level. Future studies should explore how HAIC can be better integrated into organizational practices and policies, addressing the identified gaps and overcoming the obstacles currently limiting its impact on environmental sustainability. By doing so, the potential of HAIC to drive sustainable can be fully realized, contributing to a more resilient and sustainable future.

Nevertheless, this study has several limitations. First, due to the relatively recent emergence of the term Human-AI Collaboration (HAIC), various synonymous terms exist within the field. This paper focused on terms like augmented intelligence, hybrid intelligence, and human-AI teaming and collaboration, but did not delve deeply into collaborations specifically involving deep learning and human intelligence. Second, because this study primarily concentrates on HAIC for Environmental Sustainability (ES), the impacts discussed are mainly indirect—HAIC practices influence processes, which in turn affect the environment—while direct impacts, such as those arising from the physical presence and processes of HAIC technologies, were not thoroughly explored. Future research should investigate these direct effects more comprehensively. Finally, although this paper examined HAIC's role in promoting ES, future studies should increasingly focus on strategies to enhance the environmental sustainability of HAIC itself.

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