There is AI in SustAInability – A Taxonomy Structuring AI For Environmental Sustainability

Research Paper

Feline Schnaak[1,2], Katharina Breiter[1,2,3], Henner Gimpel[1,2,3]

[1] FIM Research Center for Information Management, Augsburg, Germany
[2] Branch Business & Information Systems Engineering
of the Fraunhofer FIT, Augsburg, Germany
[3] University of Hohenheim, Chair of Digital Management, Stuttgart, Germany
{feline.schnaak,katharina.breiter,henner.gimpel}@fim-rc.de

Abstract. A lack of environmental sustainability poses threats to businesses and society. Artificial intelligence has been recognised as a promising enabler of sustainability through mitigation and adaptation efforts. While AI systems for environmental sustainability have been developed for specific contexts, and initial research has explored the broader field of AI for sustainability, there is a need to structure these initial approaches using a taxonomy. After conducting five iterations based on scientific literature and real-world examples, our multi-layer taxonomy comprises nine dimensions organised across the layers context, AI setup, and usage. We demonstrate the utility of our taxonomy by categorising the offerings of exemplary companies. By enhancing descriptive knowledge of AI for environmental sustainability, our taxonomy is a step towards a theory for analysing, enabling researchers and practitioners to holistically understand AI systems for environmental sustainability.

Keywords: Artificial Intelligence, AI for Sustainability, Environmental Sustainability, Green IS, Taxonomy

1 Introduction

As the global climate crisis intensifies, humanity needs to take immediate action to counteract and mitigate environmental degradation (IPCC, 2023). However, sustainability efforts often face significant challenges, such as delayed benefits, high-cost investments without immediate economic returns, and difficulties in measuring long-term impacts. Therefore, we need innovative solutions that tackle these challenges and enable environmental sustainability. Technological advancements play a crucial role in developing scalable solutions, with artificial intelligence (AI) emerging as a key enabler.

AI has the potential to revolutionise environmental sustainability efforts by offering data-driven insights, optimising resource use, and enhancing decision-making (e.g., Nishant et al., 2020; Schoormann et al., 2023). A striking example is the protection of the Great Barrier Reef. Researchers integrated various data sources such as underwater

20th International Conference on Wirtschaftsinformatik,
September 2025, Münster, Germany

videos, satellite images, and marine sensors into an AI-powered monitoring system to detect coral bleaching and optimise conservation strategies (Chowdhury et al., 2024).

AI's role in environmental sustainability has attracted growing scholarly attention in recent years. Research has explored the role of AI in achieving the UN's Sustainable Development Goals (SDGs), with studies assessing its impact across all 17 SDGs and generally concluding that AI systems contribute positively to their attainment (Bankhwal et al., 2024; Chaudhary, 2023; Vinuesa et al., 2020). The literature on AI applications for environmental sustainability already encompasses various AI models (Kar et al., 2022) and domains like energy, water, biodiversity, transportation, agriculture, and climate change mitigation (e.g., Berger et al., 2024; Nishant et al., 2020; Raihan et al., 2024). For instance, AI predicts residential heating energy performance (Wenninger & Wiethe, 2021), optimises carsharing incentives for sustainable transportation (Herrenkind et al., 2019), and tackles air pollution (Q. Zhu et al., 2018).

This paper's focus on environmental sustainability relates to the digital sustainability dilemma (e.g., Zimmer et al., 2024; Veit & Thatcher, 2023). Digital technologies can both advance and harm environmental sustainability, as their deployment often generates negative impacts, leading to rebound effects (Nishant et al., 2020; Veit & Thatcher, 2023). Addressing the dilemma requires simultaneously considering Green Information Technology (IT), which reduces the environmental footprint of IT infrastructure, and Green IS, which leverages digital technologies to promote sustainable practices (Zimmer et al., 2024). Both concepts have a clear focus on enhancing environmental sustainability and adhere to the broader concept of digital sustainability (Kotlarsky et al., 2023), which is defined as "the design, development, configuration, deployment and decommissioning of digital resources and artefacts towards improving the environment and economic welfare" (Rosati et al., 2024, p. 8). Thus, we recognise that using AI as Green IS for environmental sustainability brings new opportunities but also adds complexity to already challenging problems (Berente et al., 2021; Schoormann et al., 2023).

Given the rapidly growing body of research, efforts have been made to structure the field through systematic reviews and research agendas (e.g., Schoormann et al., 2023; Nti et al., 2022; Kar et al., 2022; Nishant et al., 2020). However, theoretical development remains scarce, and clearer insights are needed to guide policymakers and organisations in aligning AI interventions with sustainability frameworks, such as the SDGs (Nishant et al., 2020). This is particularly relevant given the rapid rise of AI-driven startups (Weber et al., 2022). While prior research has largely focused on AI's role in social sustainability (Schoormann et al., 2023), further investigation into its environmental applications is needed (e.g., Berger et al., 2024; Bibri et al., 2024).

Despite its potential, a lack of systematic understanding hinders the effective and responsible deployment of AI as Green IS. To enhance transparency, frameworks are needed to evaluate the design and the impact of AI systems before their large-scale deployment (Bibri et al., 2024; Vinuesa et al., 2020). However, existing research is fragmented, hindering overarching insights and future guidance. To synthesise existing AI application knowledge as basis for further research, we propose a categorisation framework for AI in environmental sustainability. We thus ask: *What are dimensions and characteristics structuring AI for environmental sustainability?*

To address this research question, we developed a multi-layer taxonomy of AI systems for environmental sustainability (AIfES), a promising approach for analysing novel and unstructured phenomena (Gregor, 2006). By enhancing descriptive knowledge and enabling the application to individual AI systems to analyse their environmental sustainability characteristics, our taxonomy supports researchers in clarifying the components of AIfES (Kundisch et al., 2022; Nickerson et al., 2013) and integrates insights from IS and non-IS literature as well as startup databases. It contributes to the academic discourse by synthesising developments across subtopics such as agriculture and energy efficiency, thereby providing a comprehensive overview of the emerging AIfES field. In addition, our taxonomy offers practical value to companies seeking to design, evaluate, or benchmark AI-based sustainability solutions, and to (non-)governmental organisations aiming to identify or promote impactful AI innovations. By providing a structured tool to analyse and categorise AIfES, we support stakeholders seeking a more systematic understanding.

2 Theoretical Background

2.1 Environmental Sustainability and Artificial Intelligence

Sustainable development is defined as meeting current needs without compromising future generations (Brundtland & Khalid, 1987) and can be framed as 'triple bottom line' of economic, social, and ecological sustainability (Elkington & Rowlands, 1999). The 17 SDGs by the United Nations (2015) operationalise the promotion of peace, prosperity, and environmental protection.

State-of-the-art IS research emphasizes the importance of achieving environmental sustainability (e.g., Rosati et al., 2024; Veit & Thatcher, 2023). With organisations playing a pivotal role in environmental protection, employing Green IS makes a difference (Melville, 2010), when diligently combined with Green IT approaches (Zimmer et al., 2024). Recently, Green IS research has explored IT-enabled sustainability transformation (Püchel et al., 2024; Xu et al., 2024), digital-sustainable co-transformation (Zimmer & Järveläinen, 2022), and twin transformation (Breiter et al., 2024). These transformations are enabled by innovative Green IS.

Acknowledging the current rise of AI, unforeseen possibilities become possible, for environmental protection and, thus, for Green IS research. Compared to other IS, state-of-the-art AI offers three promising benefits: automating repetitive tasks, extracting insights from vast unstructured data, and integrating computing resources to tackle complex problems (Nishant et al., 2020). But, employing AIfES also raises challenges, such as an overreliance on historical data in machine learning models, uncertain human behavioural responses to AI-based interventions, heightened cybersecurity risks, adverse impacts of AI applications (see also the digital sustainability dilemma), and greater difficulties in measuring effects of intervention strategies (Nishant et al., 2020). Thus, IS researchers need to investigate how AI can overcome these challenges and truly help environmental protection. The emerging field of 'Sustainable AI' advocates for AI lifecycle changes to enhance ecological integrity and social justice (van Wynsberghe, 2021), and encompasses both AI applications for sustainability ('AI for sustainability') and the sustainable design of AI systems ('sustainability of AI'). Together, these research streams address the digital sustainability dilemma (Zimmer et al., 2024). AIfES can be positioned within 'AI for sustainability.'

2.2 Structuring the Field of Artificial Intelligence for Environmental Sustainability

Previous research explored AI's potential for environmental sustainability through various approaches. First and foremost are the (a) IS articles that investigate the use of AIfES in specific contexts and serving various purposes (e.g., Herrenkind et al., 2019; L. Zhu et al., 2023), which can be understood as contributing to the emerging concept of AIfES. Second, there are (b) IS articles reviewing and structuring the broader field 'AI for sustainability' (e.g., Bracarense et al., 2022; Schober & Mattke, 2022). Third, there is (c) a vast amount of relevant research from disciplines like ecology or energy management, including specific applications and reviews (e.g., Bibri et al., 2024; Nti et al., 2022; Raihan et al., 2024). In accordance with Schoormann et al. (2023) and Bracarense et al. (2022), we perceive that the IS discipline is lagging in researching AIfES, with (a) few articles focusing on specific applications and (b) first endeavours undertaking efforts to structure the broader field 'AI for sustainability'. With our taxonomy, we intend to synthesise prior research and add a theoretical element connecting (a) and (b). We include (c), as these provide valuable insights for IS research.

3 Taxonomy Design

We designed our taxonomy following Nickerson et al. (2013) and Kundisch et al. (2022). After defining the problem (see Introduction), we identified target users: Sustainable AI researchers, companies, and (non-)governmental organisations. The taxonomy provides an overview of AIfES and enables its users to apply it to AI systems to analyse their environmental sustainability characteristics. It thus supports research, AI development, and policymaking by highlighting strengths and weaknesses in current use of AIfES. The meta-characteristic is the dimensions and characteristics of AIfES. Objective ending conditions (OCs) include: "no new dimensions or characteristics were added in the last iteration" (OC1), "every dimension is unique and not repeated" (OC2), "every characteristic is unique within its dimension" (OC3) and "at least one object is classified under every characteristic of every dimension" (OC4) (Nickerson et al., 2013). For the subjective ending conditions (SCs), we wanted the taxonomy to be concise (SC1), robust (SC2), comprehensive (SC3), extendible (SC4), and explanatory (SC5) (Nickerson et al., 2013). Following Jonas et al. (2023), we did not enforce mutual exclusivity to retain essential information. Each design iteration had either a conceptual-to-empirical or an empirical-to-conceptual approach (Nickerson et al., 2013). The former derives dimensions from theory, the latter from real-world samples. We refined the taxonomy iteratively, verifying conditions until met. Table 1 provides details.

Table 1. Overview of the Taxonomy Design Iterations

It. # C2E/ E2C	Purpose	Key Activity	Sample Size	Selection Criteria	Exclusion Examples	Major Changes	# D./C., OC/SCs not met
1 C2E	Young research field; starting with established IS knowledge for overview Journal articles used for their thorough research and review	SLR, sources: AIS' Senior Scholars' List of Premier Journals + journals in AISeL Search string[1]	47 results, thereof 6 relevant articles 1 seminal paper added due to frequent citation and high relevance	Article focuses on AI systems AI systems have a positive impact on environmental sustainability	AI not in focus (e.g., Srivastava & Shainesh, 2015) (Environmental) sustainability not in focus (e.g., Venkatesan et al., 2021)	Adding 7 dimensions *("ecological" SDG*, *environmental sustainability topic*, *technology, AI paradigm, data source, data access, end-user*) and 38 characteristics	7/38, OC1
2 C2E	Insights from only seven IS research journal articles provide a limited insights Scope expanded to include non-IS literature sources	SLR, sources: Web of Science, Scopus Search string[1], "AND taxonomy" added for fewer, more relevant results	1,009 results (without duplicates), 46 remained for full-text analysis, thereof 31 relevant articles	See It. 1	Use of taxonomies to classify species (e.g., a review of old-emerging rice diseases (Khanal et al., 2023))	Replacing dimension *technology* with *AI domain* Adding 2 dimensions (*risk assessment, data sensitivity*) and 4 related characteristics Merging and adding 9 characteristics	9/51, OC1 SC2
3 E2C	Ensure real-world applicability	Use of 20 real-world examples, sources: 2 articles from AImagazine.com (Allan, 2023) and Forbes.com (Gow, 2020) as most compelling Google search results	30 AI systems identified, thereof 20 included	Explorative online search must yield sufficient information[4] AI system for environmental sustainability must comply with our definition and be relevant	Sea Machines Robotics Inc. (2024), as the AI systems' focus is on economic sustainability, e.g., by employing autonomous command and control on workboats	Merging and renaming 5 characteristics Adding 2 characteristics	9/53, OC1 SC2
4 C2E	Capture the latest developments in IS research via conference proceedings	SLR, source: conference proceedings in AISeL Search string[1]	236 results (without duplicates), 22 remained for full-text analysis, thereof 11 relevant articles	See It. 1	Focus on Sustainability of AI (e.g., Mucha et al., 2022)	Merging 7 characteristics Adding 1 characteristic	9/50, OC1 SC2
5 E2C	Ensure and validate real-world applicability	Use of 20 real-world examples, source: Crunchbase[2] Search string[3], industry filter: 'AI'	137 AI systems identified, thereof 20 included	See It. 3 Filters:'smart city', 'environmental sustainability', 'circularity', 'climate change', 'biodiversity'	Brightest Inc. (2024), as the AI-enhanced software for companies focuses on social impact	None	9/50

[1]("sustainability" OR "environmental" OR "ecological" OR "Green IS" OR "Green IT") AND ("AI" OR "Artificial Intelligence" OR "ML" OR "Machine Learning"), applied to title, abstract, keywords; published in English between 2014 and 2024; [2]following Gimpel et al. (2018) and Jonas et al. (2023); [3]("environmental sustainability" OR "circular" OR "climate change" OR "biodiversity" OR "sustainable smart city"); [4]Sufficient information is available, when the AI system alongside its context, setup, and potential applications are mentioned

It. = Iteration; C2E = Conceptual-to-Empirical; E2C = Empirical-to-Conceptual; SLR = Systematic Literature Review; D./C. = Dimensions/Characteristics; OC = Objective Ending Condition; SC = Subjective Ending Condition

4 Multi-layer Taxonomy of AI Systems for Environmental Sustainability

This section introduces our multi-layer taxonomy structuring AIfES, as illustrated in Table 2. It specifies exclusive and non-exclusive dimensions and their amendments. Exclusive dimensions allow for the observation of exactly one characteristic at a time, like in the dimension *risk assessment,* while non-exclusive dimensions permit multiple characteristics, like in the dimension *end-user*. By integrating these layers and dimensions results a comprehensive taxonomy of AI applications in environmental sustainability. This enables users to analyse, classify, and identify systems. Grouping similar dimensions into layers simplifies the understanding of the taxonomy. The *context* layer outlines the sustainability challenges AIfES aim to address, the *AI setup* layer captures the technological foundation and data requirements, and the *usage* layer highlights potential risks and defines the system's *end users*.

Table 2. Multi-layer Taxonomy of AI Systems for Environmental Sustainability

L.	Dimension	Characteristics	E/N[1]	It.[2]
Context	"Ecological" SDG	#2 Zero hunger; #6 Clean water and sanitation; #7 Affordable and green energy; #11 Sustainable cities and communities; #12 Responsible consumption and production; #13 Climate action; #14 Life below water; #15 Life on land	N	1
Context	Environmental sustainability topic	Agriculture; Land use; Water resources; Biodiversity; (Raw) materials conservation; Waste & circularity; Energy conservation; Climate change mitigation & adaptation; Renewable energy; Transportation; IT & IS; Pollution	N	1 (4)
AI setup	AI paradigm	Symbolic; Neurosymbolic; Subsymbolic	E	1
AI setup	AI domain	Reasoning; Planning; Learning; Communication; Perception	N	1 (2)
AI setup	Data source	Open-source data sets; Online platforms; Legal documents; Scientific papers; Digitised natural science collections; Sample collection; Biophysical environment; Operating system; Artificially generated	N	1 (2,3, 4)
AI setup	Data access	Publicly available; Available after registration; Available for purchase; Internal	N	1 (2,3)
AI setup	Data sensitivity	Yes; No	E	2
Usage	Risk assessment	High risk; Not explicitly banned or listed as high risk	E	2
Usage	End-user	Governments; NGOs; Companies; Scientists in academic institutions; Privately acting individuals	N	1 (2,3)

[1] E = Exclusive dimension (one characteristic observable at a time); N = Non-exclusive dimension (potentially multiple characteristics observable at a time), [2] Iteration in which the dimension was added (revised); L = Layer; SDG = Sustainable Development Goal; IT = Information Technology; IS = Information Systems; NGO = Non-governmental organisation

4.1 The Context Layer

"Ecological" SDG. This dimension shows, which of the SDGs as defined by United Nations (2015) are addressed by implementing and using the AIfES. We only included those SDGs that pertain to the ecological aspect of sustainability, using their precise names and numbers. We put ecological in quotation marks to signal that these SDGs may also cover economic and social sustainability simultaneously (Chaudhary, 2023).

We followed the categorisation by Vinuesa et al. (2020), further refined by Schoormann et al. (2023). SDG *#6 Clean water and sanitation* was added based on our analysis of journal articles (e.g., Nishant et al., 2020; Bracarense et al., 2022; Savarimuthu et al., 2023). For instance, Bracarense et al. (2022) see a research gap in land, air, and water conservation hinting at the importance of maintaining clean waters from an ecological perspective. This finding is backed by the autonomous sea cleaning vehicle by Iwrobotx (2024) which reduces marine pollution and also benefits *#14 Life below water.*

Environmental Sustainability Topic. Ten out of the twelve characteristics of this dimension were directly adopted from the conceptualisations elaborated by Nishant et al. (2020) and refined iteratively. We added *climate change mitigation & adaptation* in the first iteration, as Bracarense et al. (2022) pointed out the possibilities of AI in this domain. In the fourth iteration, *IT & IS* was added, as Schober and Mattke (2022) highlighted the usefulness of AI for more environmentally sustainable soft- and hardware. Thereby, our taxonomy includes the sustainability of AI indirectly. These topics detail specific areas of AI application and thereby complement the *"ecological" SDG* dimension, illustrated in the following through two exemplary SDGs associated with characteristics of this dimension. For instance, both characteristics *renewable energy* and *energy conservation* can serve SDG *#7 Affordable and green energy,* despite AI being applied differently in each case, e.g., by forecasting energy production through renewable energy (SparkCognition, 2024) or by steering energy-consuming appliances that are not in use (Nokia Corporation, 2024). Further, this allows for combinations. An AI that employs computer vision (CV) to spray herbicides precisely on weeds mitigates *pollution* of the soils and groundwater and enables more sustainable *agriculture* (Blue River Technology, 2024) leading to *#12 responsible consumption and production.*

4.2 The AI Setup Layer

AI Paradigm. Even though the dimension and the three characteristics were not explicitly mentioned in the research included in the first iteration, we opted to add it directly. The underlying paradigm of an AI system offers valuable insights into its setup, with the three established paradigms being beneficial for both research and practice (Hitzler et al., 2020; Sheth et al., 2023). Each of the paradigms has distinct methodologies and capabilities, and understanding their differences is crucial for appreciating their respective strengths and limitations. *Symbolic* AI uses human-readable symbols, rules, and logic to represent knowledge and perform reasoning tasks, thereby excelling in structured data tasks and offers transparency but struggling with noise and unstructured data (Hitzler et al., 2020; Renkhoff et al., 2024). *Subsymbolic* AI employs ML and deep learning (DL) to represent knowledge as patterns in high-dimensional vectors rather than explicit symbols and excels in unstructured data tasks but tends to lack explainability (Hitzler et al., 2020; Renkhoff et al., 2024). The latest *neurosymbolic* AI approach seeks to integrate the other two paradigms, combining their strengths to develop AI systems that are robust, capable of learning, and offer explainable, transparent decision-making processes (Hitzler et al., 2020; Renkhoff et al., 2024). Thus, it holds promise for advancing AI capabilities in both algorithmic and application-level contexts (Sheth et al., 2023). With *neurosymbolic* AI combining elements of *symbolic* and *subsymbolic* AI, the characteristics are mutually exclusive. As most of the AI systems categorised in this research use ML techniques (e.g., Niittynen et al., 2020; Walk et al., 2020), the current focus of employed AI systems lies on *subsymbolic* AI.

AI Domain. The *AI domain* dimension refers to the respective AI system's capabilities and was adapted from Samoili et al. (2020), where definitions for the characteristics can be found. The two characteristics *reasoning* and *planning* involve converting data into knowledge, which entails transforming information into a format that machines can comprehend and use for representation and *reasoning*. *Planning* includes decision-making through structured planning, solution searching, and optimisation paths (Samoili et al., 2020). The three characteristics *learning, communication,* and *perception* encompass information extraction and problem-solving based on (un-)structured data (e.g., written, and oral language, images, sound), adaptation and responsiveness to changes, and behavioural prediction. Related AI subfields include ML, natural language processing (NLP), and CV. We chose an established AI classification due to the diverse methods used to categorise AI in the literature.

Data Source. The *data sources* provide information about the data's origin and demonstrate that data comes in different formats such as written language, audio records, video records, or images (e.g., Høye et al., 2021; Samoili et al., 2020; Walk et al., 2020). The characteristics come from various sources and are best explained with the help of examples. Meta Platforms Inc. used a *publicly available open-source data set* for concrete compressive strength to generate a concrete mix that reduces the use of cement without compromising strength requirements for data centre construction (Kusuma & Sudhalkar, 2022). *Online platforms* are defined by bringing their users together in places such as online marketplaces, collaborative economy platforms, or social media platforms (European Commission, 2022). An example is the citizen science portal Zooniverse, which allows laypeople to contribute to research projects in fields like medicine, physics, and social sciences, serving as a source of training data for DL models (Høye et al., 2021). *Sample collections* and *digitised natural science collections* are physical collections used by biologists, e.g., to analyse native plant or animal diversity (Høye et al., 2021; Park et al., 2020). *Legal documents* can be defined as legal texts and texts that must be published for legal reasons like patents. Venugopalan and Rai (2015) utilise NLP topic modelling techniques to analyse technological innovations in a dataset of solar photovoltaic patents. *Scientific papers* can also be a valuable input for topic modelling techniques, for example for analysing climate change research aiming to identify potential gaps (Callaghan et al., 2020). *Biophysical environment* data can be retrieved from our environment. For example, remote sensing techniques are used to collect satellite data, which serves as input for *land use* mapping using ML algorithms (Karakizi et al., 2018). Further, audio records are used for the classification of species in groups like bees for the protection of *biodiversity* (Høye et al., 2021). The *data source operating system* is defined by data generated by a system in operation, e.g., an urban rail transit system (L. Zhu et al., 2023) or a water distribution network (Zornoza, 2024). Energy usage data, which delivers insights into historical usage data for prediction (Al-Shargabi et al., 2022), is an important part of *operating system* data. *Artificially generated data* is data which has been simulated, for example for studying carsharing relocation scenarios, enabling *sustainable transportation* (Brendel et al., 2017).

Data Access. The *data access* dimension refers to the availability of the input data for the AIfES. *Publicly available* data and *internal* data were added in the first iteration following Schoormann et al. (2023). *Publicly available* data can be defined as data which is freely accessible to everyone who puts a little effort in informing him-/herself, such as information provided on websites or posts on social media, which are visible without login (Schoormann et al., 2023). *Internal* data can be defined as data which belongs to an organisation and is not made publicly available, like business documents or e-mails (Nishant et al., 2020). Data *available after registration* is typically only available by disclosing personal data and can even be reserved for specific user groups, e.g., researchers. This is the case for databases like ImageNet, which was used for aquatic bioassessment using DL by Milošević et al. (2020). Data can also be *available for purchase*, which means that a person seeking *data access* must pay for it. This may be the case for environmental intelligence platforms like tomorrow.io (2024), as their business model is to provide forecasting for different contexts.
Data Sensitivity. *Data sensitivity* measures how much protection data requires, based on the potential harm from its misuse (Rumbold & Pierscionek, 2018). It is context-dependent and must be considered independently of *data access*, as customer usage data (e.g., Donti & Kolter, 2021) or data related to critical infrastructures (e.g., Ilter & O'Daniel, 2022) must be handled with care. Proper categorisation and protection of sensitive data are essential for ethical and legal compliance (Rumbold & Pierscionek, 2018). *Data sensitivity* is not strictly binary, as distinct types of data can exhibit varying degrees of sensitivity depending on factors like regulatory frameworks (e.g., General Data Protection Regulation) applicable or the context of data sharing. Examples of non-sensitive data are *open-source data sets* like statistical population data (e.g., Papagiannis et al., 2021) as those are aggregated and *publicly available* so that anyone can make use of them for manifold purposes. However, if a company somehow possessed the data of one individual in that data set, it may well be sensitive data. We use a binary dimension, as companies or researchers must decide whether sensitive data is used when looking at all data sets used for one specific system. For example, Dayrize Ltd. (2024) provides a sustainability intelligence platform that uses *publicly available* and thus *non-sensitive* data for clients getting started on their 'sustainability journey'.

4.3 The Usage Layer

Risk Assessment. *Sensitive* data plays a key role in *risk assessment*. This dimension was added in the second iteration, inspired by Bonsón et al. (2021), who highlight AI's potential to address societal challenges like sustainable development alongside its risks of increasing disparity and restricting human freedom. Thus, the risks of employing AI necessitate ethical considerations about possible unintended consequences such as creating power asymmetries between those that employ AIfES and those effected by its use (Grewal et al., 2021). We adopted the characteristics from the EU AI Act (European Commission, 2024) and thus, draw upon their definitions. *High risk* AI systems are classified as such because they use *sensitive* data that can severely impact individuals' lives or make critical infrastructure vulnerable. AI systems *not explicitly banned or listed as high risk* usually do not use *sensitive* data and thus do not pose severe threats.

While the conversational agent promoting pro-environmental behaviour by SOORT (2024) is categorised as *not explicitly banned or listed as high risk,* AI systems employed for urban rail transport systems (L. Zhu et al., 2023) are categorised as *high risk.* The EU AI Act also introduces 'unacceptable risk,' which applies to AI systems used for social scoring and human emotion recognition (European Commission, 2024). We excluded this, as it should lead to the termination or substantial revision of the AIfES.

End-user. This specifies the target user groups of the AIfES in question. *Governments* is employed as a broad term covering government agencies (e.g., Dhaigude & Ghosh, 2023) and policymakers (e.g., Isabelle & Westerlund, 2022). Looking at *non-governmental organisations*, we specifically target those that cope with environmental preservation challenges, such as the Forest Stewardship Council (Marggraff & Venter, 2020). *Companies* comprises institutional users of all business sectors, such as farmers (e.g., Dhaigude & Ghosh, 2023) or public transport system providers (e.g., L. Zhu et al., 2023). Some AIfES (e.g., Reshma et al., 2023; Niittynen et al., 2020) also target *scientists in academic institutions.* This is not surprising, as we gathered AI systems in scientific literature. *Privately acting individuals* can be defined as individual users like consumers with a pronounced environmental consciousness seeking eco-friendly options (Henao-Rodríguez et al., 2024) or climate activists. As an example, Microsoft's AI-enhanced Planetary Computer aims to enable data-driven decision-making for *end-users* like scientists, developers, and policy makers (Microsoft Corporation, 2024).

4.4 Demonstration of the Taxonomy's Application

For exemplary purposes, we characterise an AIfES analysed in the third iteration. See & Spray™ by Blue River Technology (2024) uses robotics, CV, and DL to distinguish crops from weeds with high accuracy. Custom nozzles for tractors enable precise, plant-specific spraying, supported by software for efficient crop protection. In the *context* layer, this addresses *ecological SDGs #2 Zero hunger* by improving crop yields through preventing herbicide resistance*, #6 Clean water and sanitation*, and *#12 Responsible production and consumption* by reducing herbicide runoff. Its *environmental sustainability topics* include *agriculture, water resources, pollution*, and *biodiversity*, which is less threatened with less polluted groundwater and creeks. In the *AI setup* layer, See & Spray™ employs the *subsymbolic AI* paradigm via DL and operates in the *AI domains* of *learning* (via DL techniques) and *perception* (via CV). The *data sources* are *sample collections* from the *biophysical environment,* as See & Spray™ was first trained to distinguish green plants from the brown soil and then learned to recognise weeds which fall out of the seeding pattern. Data is *non-sensitive* as no personal information is processed, and *data access* is restricted to *internally* generated training data. Concerning the *usage* layer, See & Spray™ can be classified as *not explicitly banned or listed as high risk* and is primarily targeted at *companies* in the agricultural sector as *end-users.* The taxonomy helps Blue River Technology to assess potential for further development. For example, collecting *biophysical environment* data like wind speed can optimise herbicide application, enhancing the technology's precision.

On a side note, our taxonomy design highlighted the growing importance of the research topic. Of the 49 articles included, we found no publications between 2014-2016 and only four between 2017-2019. We noted an increasing interest from 2020 to 2023, with an average of 10.75 publications per year (2020: 13; 2021: 9; 2022: 10; 2023: 11).

5 Discussion

5.1 Theoretical Contributions

Our work contributes to theory in diverse ways. First, we enhance descriptive knowledge of AI for sustainability by presenting a taxonomy for AIfES, based on IS and non-IS literature and entrepreneurial cases. It extends Green IS research (e.g., Nishant et al., 2020; Schoormann et al., 2023) by combining deductive insights from the broader AI for sustainability field with an inductive, holistic view of AIfES beyond subtopics like *agriculture* or *energy efficiency*. We organised the fragmented yet growing AIfES landscape by integrating insights from the dynamic AI systems market. Our taxonomy enables a comprehensive understanding of AIfES and offers Green IS researchers a basis for future theorising beyond single AI systems. While rooted in Green IS, it also informs broader debates on IS artifact evaluation (Prat et al., 2015), IS innovation (Hund et al., 2021) and digital transformation (Vial, 2019).

Second, the taxonomy highlights risks and challenges of AIfES by translating AI system features into distinct, measurable, and comparable dimensions. For instance, classification within the *AI setup* layer may reveal the need for stronger data privacy if *sensitive*, *non-public* data is used. Similarly, the *data source* dimension may expose imbalances. Thus, the taxonomy promotes transparency around the opportunities and limitations of AIfES, enabling informed discussion and scholarly progress.

Third, the taxonomy clarifies AI systems' environmental impact and supports future theoretical development (Gregor, 2006). Structuring the research field revealed in the first iteration, for example, that SDG *#6 Clean water and sanitation* also involves ecological aspects, broadening its environmental sustainability relevance (Schoormann et al., 2023; Vinuesa et al., 2020). Such deeper analysis helps uncover key interrelations.

Fourth, by integrating both streams of Sustainable AI, we address the digital sustainability dilemma. While focused on AIfES, the taxonomy considers the sustainability of AI: In the third iteration, we added *IT & IS* as an *environmental sustainability topic*, implicitly including sustainably designed AI systems for environmental purposes, underlining the relevance of both streams and the need for responsible IT and IS practices.

5.2 Practical Implications

The results offer implications for companies developing or using AIfES, as well as for (non-)governmental organisations supporting progress in this field. Our work enhances understanding of AIfES and supports their systematic analysis and classification. The taxonomy helped us as author team distinguishing AI systems based on their contributions to environmental, social, and economic sustainability. (Non-)governmental organisations can apply it to assess whether AI systems genuinely promote environmental sustainability or primarily serve other goals, thereby informing evaluation frameworks, funding decisions, and policy development. For companies, the taxonomy offers practical guidance for designing, evaluating, and communicating the sustainability value of AI systems. The *context* layer clarifies the purpose of an AI system, supporting alignment with sustainability strategies. The *AI setup* layer assists in identifying technical challenges, and the *usage* layer helps define and differentiate user groups, which is crucial for tailoring services and enhancing impact. In addition, by mapping existing solutions and highlighting underexplored areas, the taxonomy can drive innovation and highlight new opportunities. More broadly, it provides a common language across technical, managerial, and sustainability stakeholders. Amid climate urgency, the taxonomy may support the responsible development and dissemination of impactful AIfES.

5.3 Limitations and Future Research

Our study's limitations suggest pathways for future research. First, we focused on employing AIfES and did not explicitly analyse the sustainability of the AI systems. Future work should strengthen the link between the two Sustainable AI streams to prevent adverse side effects. Second, we limited the taxonomy to environmental sustainability for manageability, while future research could expand it to economic and social aspects. Third, our iterations focused on AI systems with positive environmental impacts, which may introduce publication bias and overlook negative effects. Future research should consider dimensions that capture unintended impacts. Fourth, our sample of 40 carefully selected AI systems is limited. Expanding it could reveal AI archetypes, e.g., representing trends such as generative AI and large language models, clarifying interactions within the taxonomy and linking sustainability topics to AI domains. This may also expose challenges like reliance on historical data (Nishant et al., 2020). Fifth, new characteristics will likely emerge, requiring updates to keep the taxonomy relevant. Additionally, our design may be shaped by path dependencies and subjective choices, such as excluding short-lived AI algorithms. At publication, the taxonomy has only undergone internal validation by the authors. External validation through expert interviews or focus groups (Kundisch et al., 2022) would strengthen its robustness and practical value.

6 Conclusion

Advances in AI have drawn growing attention from researchers and practitioners. AI systems hold potential to support SDGs focused on ecological sustainability, such as #13 Climate action, #14 Life below water, and #15 Life on land. Given the variety of AI systems for environmental sustainability, a taxonomy is crucial for future theorising. Based on prior IS and non-IS research and a sample of 40 AI systems from three sources, we developed a taxonomy with nine dimensions and 50 characteristics across the layers: *context*, *AI setup*, and *usage*. This framework offers researchers a structured understanding of AI system features for theory-building and supports companies and (non-)governmental organisations in leveraging AI for sustainable development.

References

Al-Shargabi, A. A., Almhafdy, A., Ibrahim, D. M., Alghieth, M., & Chiclana, F. (2022). Buildings' energy consumption prediction models based on buildings' characteristics: Research trends, taxonomy, and performance measures, *Journal of Building Engineering*, **54**, 1–34.

Bankhwal, M., Bisht, A., Chui, M., Roberts, R., & van Heteren, A. (May 2024), *AI for social good: Improving lives and protecting the planet,* McKinsey & Company (Ed.).

Berente, N., Gu, B., Recker, J., & Santhanam, R. (2021). Managing Artificial Intelligence, *MIS Quarterly*, **45**(3), 1433–1450.

Berger, T., Gimpel, H., Stein, A., Troost, C., Asseng, S., Bichler, M., Bieling, C., Birner, R., Grass, I., Kollmann, J., Leonhardt, S. D., Schurr, F. M., & Weisser, W. (2024). Hybrid intelligence for reconciling biodiversity and productivity in agriculture, *Nature Food*, **5**(4), 270–272.

Bibri, S. E., Krogstie, J., Kaboli, A., & Alahi, A. (2024). Smarter eco-cities and their leading-edge artificial intelligence of things solutions for environmental sustainability: A comprehensive systematic review, *Environmental Science and Ecotechnology*, **19**, 100330.

Blue River Technology. (2024). *DELIVERING IMPACTFUL SOLUTIONS*. https://bluerivertechnology.com/our-products/ Accessed: 23.04.2024.

Bonsón, E., Lavorato, D., Lamboglia, R., & Mancini, D. (2021). Artificial intelligence activities and ethical approaches in leading listed companies in the European Union, *International Journal of Accounting Information Systems*, **43**, 1–14.

Bracarense, N., Bawack, R. E., Wamba, S. F., & Carillo, K. D. A. (2022). Artificial Intelligence and Sustainability: A Bibliometric Analysis and Future Research Directions, *Pacific Asia Journal of the Association for Information Systems*, **14**(2), 136–159.

Breiter, K., Crome, C., Oberländer, A. M., & Schnaak, F. (2024). Dynamic Capabilities for the Twin Transformation Climb: A Capability Maturity Model, *Information Systems Frontiers*, **26**(6), 2205–2226.

Brendel, A. B., Rockenkamm, C., & Kolbe, L. M. (2017). Generating Rental Data for Car Sharing Relocation Simulations on the Example of Station-Based One-Way Car Sharing, *In* T. X. Bui & R. Sprague JR. (Chairs), Proceedings of the 50th Hawaii International Conference on System Sciences, Waikoloa Village, Hawaii.

Brundtland, G. H., & Khalid, M. (1987), *Our common future*. Oxford University Press, Oxford, GB.

Callaghan, M. W., Minx, J. C., & Forster, P. M. (2020). A topography of climate change research, *Nature Climate Change*, **10**(2), 118–123.

Chaudhary, G. (2023). Environmental Sustainability: Can Artificial Intelligence be an Enabler for SDGs?, *Nature Environment and Pollution Technology*, **22**(3), 1411–1420.

Chowdhury, A., Jahan, M., Kaisar, S., Khoda, M. E., Rajin, S. M. A. K., & Naha, R. (2024). Coral Reef Surveillance with Machine Learning: A Review of Datasets, Techniques, and Challenges, *Electronics*, **13**(24), 5027.

Dayrize Ltd. (2024). *Sustainability Intelligence Unlocked*. https://dayrize.io/ Accessed: 30.04.2024.

Dhaigude, A. S., & Ghosh, R. (2023). AgriMitr: Digitalizing the Agricultural Landscape with Satellite Imaging, *Communications of the Association for Information Systems*, **52**(1), 1119–1124.

Donti, P. L., & Kolter, J. Z. (2021). Machine Learning for Sustainable Energy Systems, *Annual Review of Environment and Resources*, **46**, 719–747.

Elkington, J., & Rowlands, I. H. (1999). Cannibals with forks: The triple bottom line of 21st century business, *Alternatives Journal*, **25**(4), 42–43.

European Commission. (2022). *The Digital Services Act*. https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/europe-fit-digital-age/digital-services-act_en Accessed: 07.06.2025.

European Commission. (2024). *Regulation (EU) 2024/1689 of the European Parliament and of the Council*. https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=OJ:L_202401689 Accessed: 04.03.2025.

Gregor, S. (2006). The Nature of Theory in Information Systems, *MIS Quarterly*, **30**(3), 611–642.

Grewal, D., Guha, A., Satornino, C. B., & Schweiger, E. B. (2021). Artificial intelligence: The light and the darkness, *Journal of Business Research*, **136**, 229–236.

Henao-Rodríguez, C., Lis-Gutiérrez, J., & Angulo-Bustinza, H. (2024). Unveiling greenwashing in Colombian manufacturing: A machine learning approach, *Research in Globalization*, **8**, 1–14.

Herrenkind, B., Brendel, A. B., Lichtenberg, S., & Kolbe, L. M. (2019). Computing incentives for user-based relocation in carsharing, *In* Proceedings of the 14th International Conference on Wirtschaftsinformatik, Siegen, Germany.

Hitzler, P., Bianchi, F., Ebrahimi, M., & Sarker, M. K. (2020). Neural-symbolic integration and the Semantic Web, *Semantic Web*, **11**(1), 3–11.

Høye, T. T., Ärje, J., Bjerge, K., Hansen, O. L. P., Iosifidis, A., Leese, F., Mann, H. M. R., Meissner, K., Melvad, C., & Raitoharju, J. (2021). Deep learning and computer vision will transform entomology, *Proceedings of the National Academy of Sciences of the United States of America*, **118**(2).

Hund, A., Wagner, H.-T., Beimborn, D., & Weitzel, T. (2021). Digital innovation: Review and novel perspective, *The Journal of Strategic Information Systems*, **30**(4), 101695.

Ilter, K., & O'Daniel, B. (2022). *Using Artificial Intelligence to Aid In Getting Actionable Smart Meter Data*. https://www.xylem.com/en-uk/brands/sensus/blog/using-artificial-intelligence-to-aid-in-getting-actionable-smart-meter-data/ Accessed: 24.04.2024.

IPCC. (2023), *Climate Change 2023 Synthesis Report: Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental*

Panel on Climate Change, Lee, H., & Romero, J. (Eds.), Geneva, Switzerland.
Isabelle, D. A., & Westerlund, M. (2022). A Review and Categorization of Artificial Intelligence-Based Opportunities in Wildlife, Ocean and Land Conservation, *Sustainability*, **14**(4), 1–22.
Iwrobotx. (2024). *DORIS S1*. https://seaeramarine.com/Marine/Index?lang=de Accessed: 30.04.2024.
Jonas, C., Schmitt, K., Oberländer, A. M., & Ebel, P. (2023). Illuminating Smart City Solutions - A Taxonomy and Clusters, *In* R. De, S. Paul, S. Sarker, & V. K. Tuunainen (Chairs), Proceedings of the Forty-Fourth International Conference on Information Systems, Hyderabad, India.
Kar, A. K., Choudhary, S. K., & Singh, V. K. (2022). How can artificial intelligence impact sustainability: A systematic literature review, *Journal of Cleaner Production*, **376**, 1–17.
Karakizi, C., Karantzalos, K., Vakalopoulou, M., & Antoniou, G. (2018). Detailed Land Cover Mapping from Multitemporal Landsat-8 Data of Different Cloud Cover, *Remote Sensing*, **10**(8), 1–25.
Kotlarsky, J., Oshri, I., & Sekulic, N. (2023). Digital Sustainability in Information Systems Research: Conceptual Foundations and Future Directions, *Journal of the Association for Information Systems*, **24**(4), 936–952.
Kundisch, D., Muntermann, J., Oberländer, A. M., Rau, D., Röglinger, M., Schoormann, T., & Szopinski, D. (2022). An Update for Taxonomy Designers, *Business & Information Systems Engineering*, **64**(4), 421–439.
Kusuma, J., & Sudhalkar, A. (2022). *Green concrete: Using AI to reduce concrete's carbon footprint*. Facebook. https://tech.facebook.com/engineering/2022/4/sustainable-concrete/ Accessed: 23.04.2024.
Marggraff, P., & Venter, M. P. (2020). Monitoring of Namibian Encroacher Bush Using Computer Vision, *AgriEngineering*, **2**(2), 213–225.
Melville, N. P. (2010). Information Systems Innovation for Environmental Sustainability, *MIS Quarterly*, **34**(1), 1–21.
Microsoft Corporation. (2024). *Microsoft | Planetary Computer Applications*. https://planetarycomputer.microsoft.com/applications Accessed: 25.04.2024.
Milošević, D., Milosavljević, A., Predić, B., Medeiros, A. S., Savić-Zdravković, D., Stojković Piperac, M., Kostić, T., Spasić, F., & Leese, F. (2020). Application of deep learning in aquatic bioassessment: Towards automated identification of non-biting midges, *The Science of the Total Environment*, **711**, 1–7.
Nickerson, R. C., Varshney, U., & Muntermann, J. (2013). A method for taxonomy development and its application in information systems, *European Journal of Information Systems*, **22**(3), 336–359.
Niittynen, P., Heikkinen, R. K., & Luoto, M. (2020). Decreasing snow cover alters functional composition and diversity of Arctic tundra, *Proceedings of the National Academy of Sciences of the United States of America*, **117**(35), 21480–21487.

Nishant, R., Kennedy, M., & Corbett, J. (2020). Artificial intelligence for sustainability: Challenges, opportunities, and a research agenda, *International Journal of Information Management*, **53**, 1–13.

Nokia Corporation. (2024). *AVA - Energy Efficiency*. https://www.nokia.com/networks/bss-oss/ava/energy-efficiency/ Accessed: 23.04.2024.

Nti, E. K., Cobbina, S. J., Attafuah, E. E., Opoku, E., & Gyan, M. A. (2022). Environmental sustainability technologies in biodiversity, energy, transportation and water management using artificial intelligence: A systematic review, *Sustainable Futures*, **4**, 100068.

Papagiannis, F., Gazzola, P., Burak, O., & Pokutsa, I. (2021). A European household waste management approach: Intelligently clean Ukraine, *Journal of Environmental Management*, **294**, 1–9.

Park, D. S., Willis, C. G., Xi, Z., Kartesz, J. T., Davis, C. C., & Worthington, S. (2020). Machine learning predicts large scale declines in native plant phylogenetic diversity, *The New Phytologist*, **227**(5), 1544–1556.

Prat, N., Comyn-Wattiau, I., & Akoka, J. (2015). A Taxonomy of Evaluation Methods for Information Systems Artifacts, *Journal of Management Information Systems*, **32**(3), 229–267.

Püchel, L., Wang, C., Buhmann, K., Brandt, T., Schweinitz, F. von, Edinger-Schons, L. M., vom Brocke, J., Legner, C., Teracino, E., & Mardahl, T. D. (2024). On the Pivotal Role of Data in Sustainability Transformations, *Business & Information Systems Engineering*, **66**(6), 831–848.

Raihan, A., Paul, A., Rahman, M. S., Islam, S., Paul, P., & Karmakar, S. (2024). Artificial Intelligence (AI) for Environmental Sustainability: A Concise Review of Technology Innovations in Energy, Transportation, Biodiversity, and Water Management, *Journal of Technology Innovations and Energy*, **3**(2), 64–73.

Renkhoff, J., Feng, K., Meier-Doernberg, M., Velasquez, A., & Song, H. H. (2024). A Survey on Verification and Validation, Testing and Evaluations of Neurosymbolic Artificial Intelligence, *IEEE Transactions on Artificial Intelligence*, **5**(8), 3765–3779.

Reshma, B., Rahul, B., Sreenath, K., Joshi, K., & Grinson, G. (2023). Taxonomic resolution of coral image classification with Convolutional Neural Network, *Aquatic Ecology*, **57**(4), 845–861.

Rosati, P., Lynn, T., Kreps, D., & Conboy, K. (2024). Digital Sustainability: Key Definitions and Concepts. In T. Lynn, P. Rosati, D. Kreps, & K. Conboy (Eds.), *Palgrave Studies in Digital Business & Enabling Technologies. Digital Sustainability: Leveraging Digital Technology to Combat Climate Change* (pp. 1–24). Springer Nature Switzerland; Imprint Palgrave Macmillan.

Rumbold, J. M., & Pierscionek, B. K. (2018). What Are Data? A Categorization of the Data Sensitivity Spectrum, *Big Data Research*, **12**, 49–59.

Samoili, S., López Cobo, M., Gómez, E., Prato, G. de, Martínez-Plumed, F., & Delipetrev, B. (2020), *AI Watch. Defining Artificial Intelligence. Towards an operational definition and taxonomy of artificial intelligence,* Publications Office of the European Union (Ed.), Luxembourg.

Savarimuthu, B. T. R., Corbett, J., Yasir, M., & Lakshmi, V. (2023). Improving Information Systems Sustainability by Applying Machine Learning to Detect and Reduce Data Waste, *Communications of the Association for Information Systems*, **53**, 189–213.

Schober, L.-M., & Mattke, J. (2022). AI for Sustainability in Organisations: A Literature Review, *In* G. Davis, S. Brown, & M. Subramani (Chairs), Proceedings of the Twenty-eighth Americas Conference on Information Systems, Minneapolis (MN) USA.

Schoormann, T., Strobel, G., Möller, F., Petrik, D., & Zschech, P. (2023). Artificial Intelligence for Sustainability—A Systematic Review of Information Systems Literature, *Communications of the Association for Information Systems*, **52**, 199–237.

Sheth, A. N., Roy, K., & Gaur, M. (2023). Neurosymbolic AI - Why, What, and How, *ArXiv*. https://api.semanticscholar.org/CorpusID:258426912

SOORT. (2024). *We lead the way to responsible consumption*. https://soort.eco/ Accessed: 30.04.2024.

SparkCognition. (2024). *SparkCognition Industrial AI Suite for Renewables*. https://www.sparkcognition.com/products/industrial-ai-suite/renewables/ Accessed: 23.04.2024.

tomorrow.io. (2024). *Make better operational decisions with weather and climate security templates*. https://www.tomorrow.io/industry-templates/dashboard/5fa19-irrigation/ Accessed: 24.04.2024.

United Nations. (2015), *A/RES/70/1—Transforming our world: The 2030 agenda for sustainable development.*, pp. 1–35. https://sdgs.un.org/2030agenda

van Wynsberghe, A. (2021). Sustainable AI: AI for sustainability and the sustainability of AI, *AI and Ethics*, **1**(3), 213–218.

Veit, D. J., & Thatcher, J. B. (2023). Digitalization as a problem or solution? Charting the path for research on sustainable information systems, *Journal of Business Economics*, **93**(6-7), 1231–1253.

Venugopalan, S., & Rai, V. (2015). Topic based classification and pattern identification in patents, *Technological Forecasting and Social Change*, **94**, 236–250.

Vial, G. (2019). Understanding digital transformation: A review and a research agenda, *The Journal of Strategic Information Systems*, **28**(2), 118–144.

Vinuesa, R., Azizpour, H., Leite, I., Balaam, M., Dignum, V., Domisch, S., Felländer, A., Langhans, S. D., Tegmark, M., & Fuso Nerini, F. (2020). The role of artificial intelligence in achieving the Sustainable Development Goals, *Nature Communications*, **11**(1), 233.

Walk, J., Kühl, N., & Schäfer, J. (2020). Towards Leveraging End-of-Life Tools as an Asset: Value Co-Creation based on Deep Learning in the Machining Industry, *In* T. X. Bui (Chair), Proceedings of the 53rd Hawaii International Conference on System Sciences, Maui (Hawaii), USA.

Weber, M., Beutter, M., Weking, J., Böhm, M., & Krcmar, H. (2022). AI Startup Business Models, *Business & Information Systems Engineering*, **64**(1), 91–109.

Wenninger, S., & Wiethe, C. (2021). Benchmarking energy quantification methods to predict heating energy performance of residential buildings in Germany, *Business & Information Systems Engineering*, **63**(3), 223–242.

Xu, L., Du, W., Pan, S. L., Send, H., & Grosse, M. (2024). Information systems-enabled sustainability transformation: A study of an energy self-sufficient village in Germany, *Information Systems Journal*, **34**(4), 1402–1424.

Zhu, L., Chen, C., Wang, H., Yu, F. R., & Tang, T. (2023). Machine Learning in Urban Rail Transit Systems: A Survey, *IEEE Transactions on Intelligent Transportation Systems*, 1–26.

Zhu, Q., Wang, T., Wu, Y., & Chai, J. (2018). A Hybrid Model to Analyze Air Pollution Spread Scales in Xi'an and Surrounding Cities, *In* Proceedings of the Wuhan International Conference on e-Business 2018.

Zimmer, M. P., & Järveläinen, J. (2022). Digital–sustainable co-transformation: introducing the triple bottom line of sustainability to digital transformation research, *In* IFIP International Conference on Human Choice and Computers, Tokyo, Japan.

Zimmer, M. P., Paul, K., & Drews, P. (2024), *Greenpeace's Digital Transformation: A Case of Digital–Sustainable Co-Transformation,* Leuphana University Lüneburg, & Greenpeace e.V. (Eds.), Lüneburg/Hamburg.

Zornoza, M. (2024). *Solve issues related to water resources using Fracta*. https://www.kurita.eu/de/solve-water-resources-issues-with-fracta/ Accessed: 23.04.2024.