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A Theoretical Review on AI Affordances for Sustainability

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Completed Research

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Abstract

Artificial Intelligence (AI) shows great potential to tackle environmental sustainability issues that are critical to the survival of Humanity and Planet Earth. However, the development and use of AI causes indirect emissions leading to detrimental effects on the environment. Therefore, it is important for organizations, researchers, and practitioners in the Information Systems (IS) domain to understand both the positive and negative effects of AI on the environment. This article contributes to this topic by performing a theoretical review of literature at the intersection of AI and Sustainability to determine the current research streams. Further, this article adopts the affordance theory as a theoretical lens with the goal to identity the affordances of Sustainable AI – a field which encompasses the research areas 'AI for Sustainability' as well as 'Sustainability of AI' – in the Green IS community. The identified affordances would enable researchers and practitioners to design and use Sustainable AI systems.

Keywords

Artificial Intelligence, Sustainability, Affordance Theory, Theoretical Review.

Introduction

Sustainability is the greatest challenge for Humanity in the 21st century. With its ability to solve complex problems with data-driven methods, artificial intelligence (AI) is a promising technology that can help organizations to achieve their environmental sustainability goals (Nishant et al. 2020). Especially, the use of AI by organizations to build consumer products and services is of utmost importance as production and consumption of goods and services in the economy is a major cause of environmental degradation (United Nations 2015). Although several studies (for e.g., Nishant et al. (2020), Rolnick et al. (2019)) elicit the applications of AI in an organizational setting to improve sustainability, few recent studies such as Schwartz et al. (2019) and Strubell et al. (2020) have also highlighted the negative environmental impact of developing and deploying complex AI models in the sub-domains of machine learning and deep learning. In their article, Strubell et al. (2020) estimate that the process of training a state-of-the-art deep learning model in natural language processing produces emissions of approximately 300,000 kgs of carbon-dioxide-equivalents, which is equivalent to the lifetime emissions produced by five cars. This high carbon footprint results from complex deep learning problems requiring high computational requirements for training that can only be satisfied by data centers (Strubell et al. 2020). Thus, organizations should understand the interdependencies between AI and Sustainability, and consider not just the environmental benefits of AI-based solutions but also the environmental costs associated with development and deployment of such solutions.

To address this, the term 'Sustainable AI' was introduced by van Wynsberghe (2021) as an umbrella term that encompasses the field that uses AI for sustainability as well as the field that deals with environmental sustainability of AI itself. Despite the emerging interest in Sustainable AI and several calls to foster sustainability as a core research imperative in IS (Gholami et al. 2016; Seidel et al. 2017), the field at the intersection of AI and Sustainability has been scantily studied in IS literature (Nishant et al. 2020) leaving theory development at the intersection of AI and environmental sustainability as a critical research gap. In this article, we aim to bridge this gap by identifying the current research streams at the intersection of AI and Sustainability. Further, we adopt the affordance theory as a theoretical lens to determine the action possibilities of AI for Sustainability. Affordance theory was first proposed by Gibson (1977) in the field of ecological psychology to explain the action possibilities offered by material objects in the environment to an animal. IS researchers have since adopted the theory in the fields of Green IS (for e.g., in Henkel et al. (2017) and Seidel et al. (2013)), digital innovation (for e.g., in Chan et al. (2019) and Trocin et al. (2021)), etc. to investigate the organizational changes enabled by information technology (IT) artifacts (Volkoff and Strong 2013). Accordingly, IS researchers have interpreted affordances as action possibilities offered by an IT artifact to a goal-oriented individual or organizational actor (Markus and Silver 2008; Volkoff and Strong 2013). This makes affordance theory a suitable lens for investigating the affordances offered by an AI artifact to an organizational actor whose goal is to achieve environmental sustainability. In essence, the article focuses on answering the following research questions (RQs):

> **RQ 1:** What are the current research streams at the intersection of AI and Sustainability?
>
> **RQ 2:** What are the affordances of AI for Sustainability?

We follow the approach of a theoretical review, which aims to bring together diverse streams of research using structured methodologies to discover patterns that facilitate future developments in the emerging field (Paré et al. 2015; Webster and Watson 2002). To answer RQ1, we identify relevant literature in Sustainable AI using a systematic literature review (SLR) method and synthesize them to identify thematic research streams. For RQ2, we further explore the identified literature to determine the various affordances of AI for Sustainability.

Affordance Theory in IS Research

The explanatory power of affordance theory lies in the fact that it attributes the emergence of affordances not just to the material properties of the IT artifact and the actor but also to the relationship between IT artifacts and the actor (Leonardi 2011; Markus and Silver 2008). For instance, the social networking platform LinkedIn offers job searching affordances for graduates and candidate searching affordances for recruiters. The mere emergence of affordances does not guarantee the affordance outcomes, but the affordances have to be first perceived and then actualized by the actor (Chemero 2003). Within the field of Green IS, Seidel et al. (2013), Recker (2016), and Henkel et al. (2017) have previously used affordance theory to outline the affordances of Green IS for organizational sustainability transformations. Seidel et al. (2013) identified organizational sensemaking affordances (information democratization and reflective disclosure) and sustainability practicing affordances (output management and delocalization) arising from material properties of IS artifacts, management interventions and actor properties. Building upon this, Henkel et al. (2017) determined that material properties giving rise to sustainability sensemaking affordances may emerge at either intra- or inter-organizational level. While these studies have contributed to both Green IS literature and affordance theory, they focus on affordances enabling sustainability but lack research on the constraints restricting the actualization of those affordances. Such work on affordances and constraints has been carried out in prior research in analyzing education systems (Kennewell 2001), feedback apps (Stoeckli et al. 2019), chatbots (Stoeckli et al. 2020). Another significant concept that has not received enough research focus in IS is the concept of negative affordances, also introduced by Gibson (1977). Gibson noted that the objects in the environment offer benefits as well as injuries to the animal and termed them as positive and negative affordances. Leonardi (2011) also observed that the action possibilities offered by an IT artifact can have both positive and negative consequences to the achievement of affordance outcomes. Several authors (for e.g., Maier and Fadel (2007), Maier et al. (2009), Srivastava and Shu (2013)) in the field of Engineering Design have focused on both positive and negative affordances arising from actor-artifact interaction. Srivastava and Shu (2013) suggested that products designed for encouraging environmentally conscious behaviour must achieve a balance between positive affordances that persuade the users towards environmentally conscious behaviour and negative affordances that push users towards wasteful behaviour. As evident from the Introduction section, various articles have pointed out the positive and negative effects of AI for environmental sustainability. Therefore, to design and use Sustainable AI systems it is important to understand the positive and negative affordances of AI as well as the respective constraints and mitigators to achieve environmental sustainability.

Literature Search

The article uses the SLR method suggested by Webster and Watson (2002) as shown in Figure 1. In the first step, the definition of search criteria included the specification of keywords and databases. To ensure a multidisciplinary perspective of research at the intersection of AI and Sustainability, multiple research outlets were considered in addition to the Basket of Eight journals suggested by the Association of Information Systems (AIS). To add boundary conditions to the literature search, certain inclusion and exclusion criteria were set. Since the computational requirements for training AI models is reported to have grown 300,000 times between 2012 and 2018 (Amodei et al. 2018), we only include articles from the last five years to reflect the state-of-the-art AI models in use today. Since this article aims to approach Sustainable AI from an organizational context, the boundary conditions are set to only cover applications involving consumer products and services and exclude articles focusing on non-commercial applications such as biodiversity and water conservation. The fourth step involved a final selection of articles where only the articles whose central theme revolved around environmental sustainability and AI were selected. In the fifth step, gray literature and further research articles based on forward/backward search were manual added. This resulted in a total of 41 articles without claiming exhaustiveness.

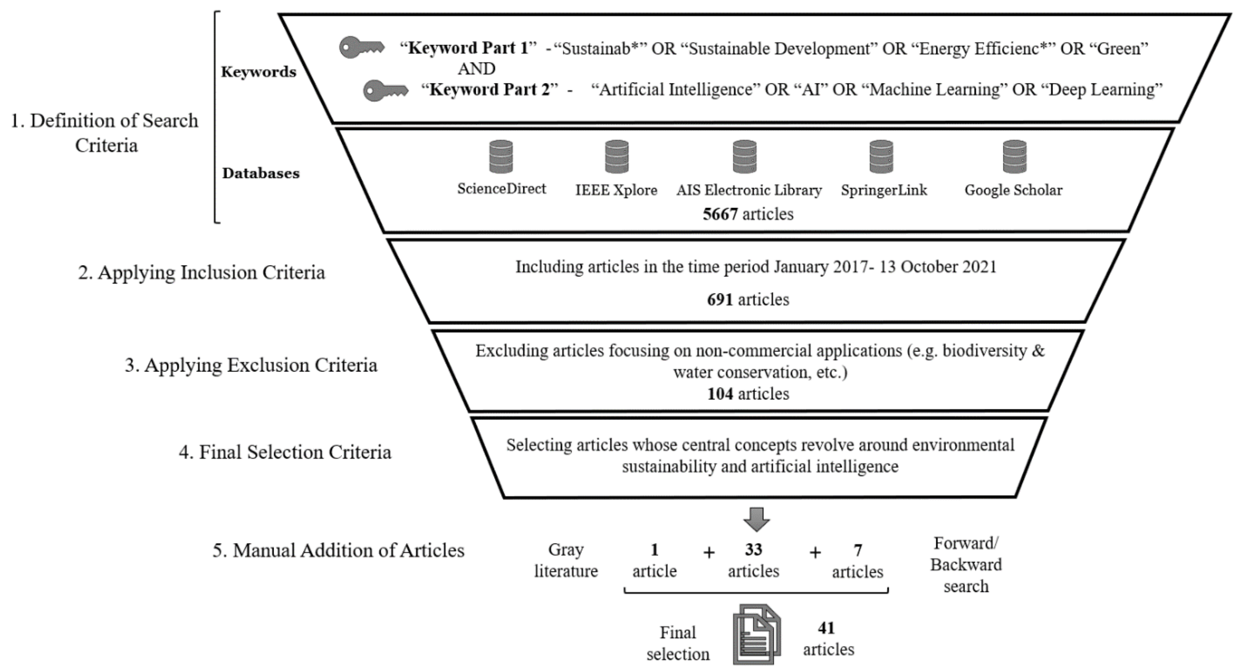

Figure 1. Literature Selection using Systematic Literature Review Process

Synthesis of Literature

To synthesize the literature identified in the previous section, we use a positivist approach called concept-centric content analysis (Paré et al. 2015), which involves analyzing deep structures in a text to cluster research based on their thematic concepts (Duriau et al. 2007). The primary research streams that are evident at the intersection of AI and Sustainability are similar to the definition of Sustainable AI by van Wynsberghe (2021) and represent positive and negative relationships between AI and Sustainability respectively:

1. **AI for Sustainability** which involves the application of AI to improve environmental sustainability

2. **Sustainability of AI** which involves the sustainable development and deployment of AI

When articles discussed both aspects, they were placed in the stream which suits them the most. Finally, 22 articles were categorized into the stream 'AI for Sustainability' and 19 articles were categorized into the stream 'Sustainability of AI'.

AI for Sustainability

It is evident from the literature that the organizational use-cases of AI for Sustainability range from product development, manufacturing, supply chains, business models to applications in strategy and decision making. The literature in this research stream is synthesized and clustered into four categories - three categories based on the product lifecycle and a fourth category to include the literature that discusses the business processes concerning the organization. It is to be noted that the classifications of the articles under the four categories are not mutually exclusive.

AI for Sustainable Conception

The articles in this category discuss the use of AI for ideation, materials as well as product development and how such use enhances environmental sustainability. Articles such as Hardian et al. (2020), Bertoni et al. (2018) and Kazi et al. (2017) present use-cases of AI in optimizing the development of materials and products, which are otherwise resource-intensive processes. Other articles such as Abediniangerabi et al. (2021), Goh et al. (2021) and Koeppe et al. (2018) suggest that AI-based numerical simulations are more computationally efficient and have high potential to replace conventional physics-based simulations in structural and aerodynamic design. The use of AI for Sustainable Conception can be attributed to its ability to deal with high-dimensional design and process parameters (Goh et al. 2021; Hardian et al. 2020) and determine the complex non-linear relationships between those parameters (Abediniangerabi et al. 2021); as well as its predictive ability to learn and expose hidden patterns and complex multi-parameter interactions (Abediniangerabi et al. 2021; Goh et al. 2021; Hardian et al. 2020). However, the predictive ability is also limited by the quality and quantity of data available, for which sensors with high resolution, high data acquisition rate and efficient data compression techniques are required (Goh et al. 2021).

AI for Sustainable Production

The articles in this category focus on using AI models for improving sustainability in production processes such as manufacturing, assembly, and logistics. AI models in combination with IoT sensors and BDA are used in manufacturing to help organizations in achieving high quality of products as well as economic and environmental benefits (Ghahramani et al. 2020). Several articles elaborate the AI use-cases in preventive maintenance (Mao et al. 2019), intelligent manufacturing systems (He and Bai 2021), and for determining optimal process parameters (Goh et al. 2021; Preez and Oosthuizen 2019; Tai et al. 2020) to enable low-carbon design, resource-efficient production and waste reduction. Sishi and Telukdarie (2021) report the uses of AI in supply chain for optimizing energy consumptions. AI could contribute to these cases because of its ability to convert data into real-time insights (Ghahramani et al. 2020; Tai et al. 2020); capacity to identify hidden patterns in high dimensional datasets and visualize them (Ghahramani et al. 2020; Mao et al. 2019); learning, reasoning and inference capabilities (He and Bai 2021; Mao et al. 2019); and ability to recognize non-linear relationships among different parameters (Ghahramani et al. 2020) and optimize them (Preez and Oosthuizen 2019; Tai et al. 2020).

AI for Sustainable Consumption

The articles in this category focus on improving environmental sustainability of products and services during their usage and end-of-life. AI use-cases include demand responsive systems for energy optimization (Mabina et al. 2021), generating insights based on customer's use of products (Alcayaga et al. 2019), and predicting future consumption patterns (Watson 2017) in order to avoid resource wastage. Haftor et al. (2021) note that such use of AI for improving accuracy of product and service offerings provided for consumers leads to increased value to consumers. However, the advantages of AI in these use cases are restricted by the availability of high quality training data (Mabina et al. 2021).

AI for Sustainable Business Processes

Some articles discuss the use-cases of AI in Sustainable Business Processes which include decision-making (Di Vaio et al. 2020), organizational sensemaking (Nishant et al. 2020), supply chain management (Wang and Zhang 2020), and sustainability performance assessment (Asrol et al. 2021). Such use of AI not only presents organizations with opportunities to reduce their environmental footprint (Kuo and Smith 2018), but also has economic benefits (Wang and Zhang 2020). However, the use of AI is limited by uncertain and imprecise data (Asrol et al. 2021). Also, Galaz et al. (2021) presented various systemic risks in the form of biases such as training data bias and transfer context bias associated with the use of AI for Sustainability.

Sustainability of AI

The research stream 'Sustainability of AI' has been underexplored in the literature because of the highly interdisciplinary nature of the topic. This research stream is concerned with reducing the carbon footprint of development and deployment of AI models. There have been efforts to measure and improve the energy-efficiency of different type of AI systems that involves innovative AI architectures, model training and inference methods. The literature in this area mostly involves reporting and improving the energy efficiency of deep learning models for natural language processing and computer vision tasks. The articles are clustered into three categories based on different phases of the AI lifecycle: AI Design, AI Training and AI Inferencing. The classifications of the articles under the three categories are not mutually exclusive.

Sustainability of AI Design

The articles in this category discuss various techniques for reducing the carbon footprint of AI models through improvements in their design. Many articles propose measures to improve energy efficiency of Convolutional Neural Networks (CNNs), a class of deep learning algorithms used, for instance, in computer vision tasks such as image classification and object detection. This is highly relevant since CNNs have high computational complexity and thus high energy consumption (NVIDIA 2015), which leads to higher contribution to GHG emissions. Many articles (e.g., Alemdar et al. (2017), Loni et al. (2019), Strubell et al. (2020)) suggest methods to minimize energy consumption and the resulting carbon footprint through:

1. pruning network weights, where parameters with the lowest impact on output are removed
2. development of computationally efficient AI algorithms and architectures
3. using specialized hardware for training or using hardware-adapted AI models

The experiments of Yang et al. (2017) and Li et al. (2016) noted that convolutional layers in a CNN consumer nine times more energy than fully connected layers. Alemdar et al. (2017) introduce Ternary Neural Networks (TNNs) with a specialized hardware architecture that has three times better energy efficiency with respect to the state-of-the-art algorithms on benchmark datasets, while also improving accuracy.

Sustainability of AI Training

The articles in this category discuss methods for training the AI models in an environmentally sustainable way. For instance, Schwartz et al. (2019) establish that the computational and environmental costs of training an AI model are directly proportional to 3 factors: the cost of training the model on a single example (E), the size of the training dataset (D) and the number of hyperparameter tuning experiments (H), as shown below:

$$\text{Environmental Cost} \propto E.D.H$$

Articles such as Li et al. (2016) and Tang et al. (2019) describe the effect of power management settings such as dynamic voltage and frequency scaling (DVFS) on energy consumption for training AI models. Alemdar et al. (2017) suggest that the use of a teacher-student approach for training the TNNs can potentially reduce their carbon footprint. Various measures are suggested in literature (e.g., Henderson et al. (2020), Lacoste et al. (2019), Wolff Anthony et al. (2020), Zhu et al. (2021)) to mitigate the harmful environmental effects during AI training:

1. Running experiments in low carbon-intensity regions and datacenters
2. Incentivizing energy-efficient research with leaderboards

3. Reporting of efficiency metrics along accuracy metrics
4. Use of custom-built and efficient hardware during training and deployment
5. Trading-off energy consumption and accuracy
6. Pruning AI models and trimming weights to reduce model complexity

Sustainability of AI Inference

While training is done rarely, the inferencing and retraining processes are important after deployment of the AI model as they run several times on millions of edge devices in use (Lenherr et al. 2021) and constitute 80-90% of AI lifecycle costs (Freund 2019). The need for high accuracy in inferencing also increases inferencing time (Bianco et al. 2018) and hence the energy consumption. Spelda and Stritecky (2020) suggest the addition of two more factors - the number of computational operations per inference (C) and the total number of future inferences (I)- to the equation presented by Schwartz et al. (2019):

$$\text{Environmental Cost} \propto E.D.H.C.I$$

They recommend that number of computations per inference should be limited to reduce environmental costs. Qiu et al. (2020) and Savazzi et al. (2021) suggest the use of federated learning (FL), a collaborative technique where retraining AI models are shared and distributed among edge devices with low energy consumption. However, they state that accuracy was a trade-off to optimize energy efficiency. Zhu et al. (2021) and Lenherr et al. (2021) suggest that well-designed edge devices can outperform cloud-based CPUs and GPUs due to their short latency and very low energy consumption.

Sustainable AI Affordances

In this section, we answer RQ2 by further interpreting the synthesized body of knowledge with the affordance lens to identify AI's material properties, positive affordances and their constraints, and negative affordances and their mitigators for achieving environmental sustainability as shown in Figure 2.

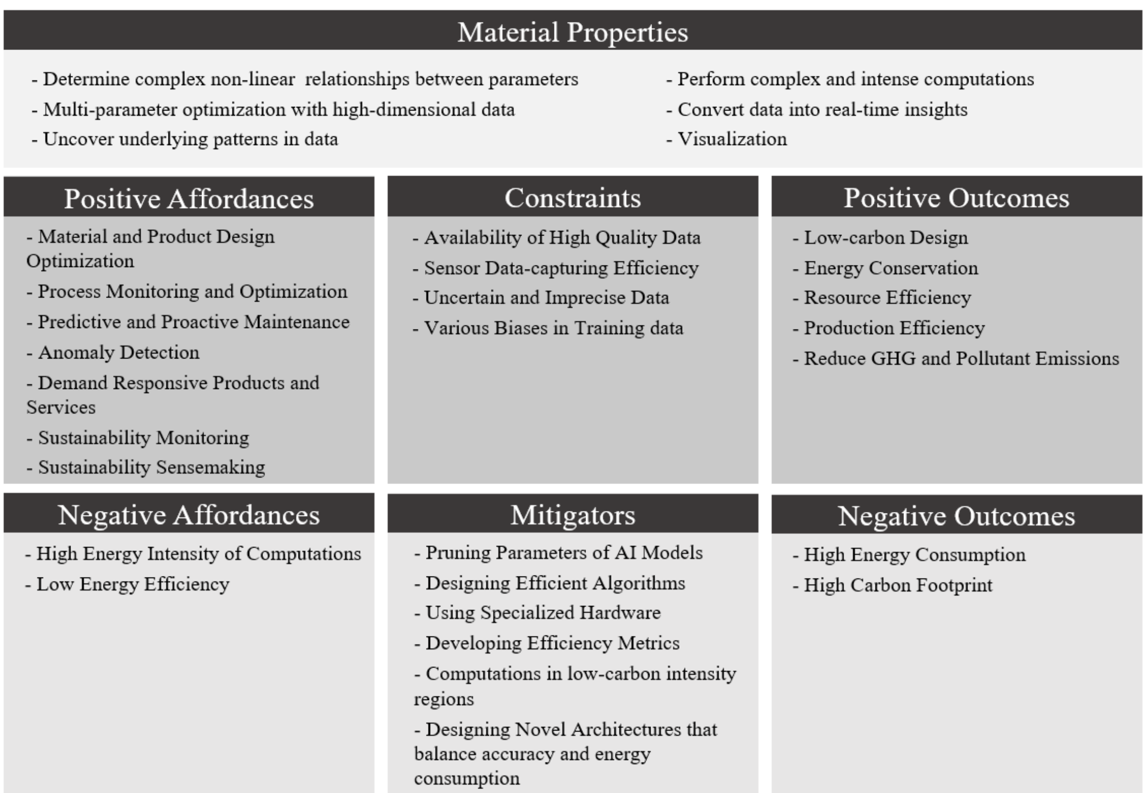

Figure 2. Interpreting Sustainable AI with an Affordance Lens

Positive affordances (e.g., material and product design optimization) of AI when actualized result in positive outcomes for environmental sustainability (e.g., low-carbon design). But this actualization of positive affordances is restricted by constraints (e.g., availability of high-quality data), which determine the degree of achievement of the positive outcomes. Negative affordances (e.g., low energy efficiency) when actualized lead to negative outcomes for environmental sustainability (e.g., high energy consumption). However, there are some mitigators (e.g., designing efficient algorithms) which could attenuate or dampen the effects of such negative affordances thus reducing the negative outcomes. A noteworthy observation is that the same material properties of AI give rise to positive as well as negative affordances. It is evident that in order to achieve positive outcomes for environmental sustainability, organizations should take efforts to reduce constraints for the positive affordances and mitigate the negative affordances. AI researchers, developers, and practitioners should therefore consider this polarity of affordances before designing or using AI. For example, AI developers could design AI systems in such a way to increase the positive affordances and reduce the negative affordances for sustainability use-cases.

Discussion and Conclusion

Climate change and sustainability are grand challenges that need to be solved and the role of AI as an enabler or inhibitor for environmental sustainability is a potential area of research for IS scholars and practitioners. This article contributes to academia by conducting a theoretical review to synthesize research at the intersection of AI and Sustainability from various disciplines and identify various affordances of AI for achieving environmental sustainability. In addition to identifying the positive affordances for sustainability that are generally discussed in Green IS literature, we also identify their constraints as well as negative affordances and their mitigators. In this process, we determine that the focus of prior research on Sustainable AI Affordances is mostly on the technical side. However, IS as a research discipline is concerned with the socio-technical aspects of ICTs – with consideration to the organizations and individuals that develop and deploy ICTs (Recker 2014). This leaves a critical research gap for IS researchers to explore the concept of Sustainable AI Affordances from a socio-technical perspective. While the relationship between the affordances, their constraints and mitigators, and the affordance outcomes seem linear based on prior research, future research should focus on exploring any potentially non-linear and complex interrelationships between the positive and negative affordances as well as the constraints and mitigators, and how they interact to give rise to the affordance outcomes. Since affordances arise from the relationship between the actor and the artifact, it is also important that future research focuses on determining the properties of organizational actors who have the goal of achieving environmental sustainability and the challenges they face in actualizing Sustainable AI affordances.

Based on this discussion, we propose three RQs for future research as shown below:

> **RQI**: What are the positive and negative socio-technical affordances of AI for environmental sustainability, and their respective constraints and mitigators?
>
> **RQII**: How are the various positive and negative affordances of Sustainable AI related to each other and how do they affect the affordance outcomes for environmental sustainability?
>
> **RQIII**: What are the properties of organizational actors and what challenges do they face in actualizing the affordances of AI for environmental sustainability?

We further recommend longitudinal studies in the area of Sustainable AI as well as extending the idea of Sustainable AI to include other dimensions of sustainability such as social and economic sustainability to attain a holistic view on leveraging AI for achieving sustainability. While the affordance theory provides a suitable theoretical lens for investigating the interplay of AI and organizational agencies for achieving environmental sustainability, we also recommend researchers to adopt other theoretical lenses to answer these RQs and develop mid-range theories. This ensures multiple perspectives on the topic of Sustainable AI, which are needed to explore the complex nature of sustainability issues and also capture the interactions between AI artifacts and organizational actors (Nishant et al., 2020). With the rapid growth of AI and importance of sustainability, this field of Sustainable AI needs groundbreaking research and this article aims to be a catalyst by recommending a socio-technical approach for Sustainable AI.

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