AI-Based Decision Support Systems for Sustainable Development

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Abstract

Making sustainable development happen is one of the most important and hardest to tackle issues of the twenty-first century. It takes a choice of understanding to be made under uncertainty and in the midst of complicated situations. Conventional Decision Support Systems (DSSs) have been unable to meet sustainability challenges owing to their inability to handle large-scale, different types of data efficiently. The reliance on the integration of Artificial Intelligence (AI), especially machine learning and data analytics, to DSS has emerged as a way to make decision-making smart, flexible, and based on data [2], [3].

This document provides an exhaustive examination of the AI-based Decision Support Systems (AI-DSS) used for sustainable development. A conceptual schema is suggested to display AI's contribution to decision-making focused on sustainability. The primary fields of application are reviewed in terms of the advantages, shortcomings, and consequences of the AI-DSS, thereby paving the way for the identification of future research directions that could potentially strengthen the AI-DSS of sustainable development both in terms of effectiveness and responsible use.

Keywords: Artificial Intelligence, Decision Support Systems, Sustainable Development, Machine Learning, Sustainability Analytics, Smart Systems.

1. Introduction

Sustainable development involves a three-dimensional concept that includes economic growth, environmental protection, and social well-being and satisfies present needs without jeopardizing the needs of the future [1]. The definition by the Brundtland Commission is still considered a primary one, highlighting the concepts of intergenerational equity and resource management for the long term [1]. Moreover, the United Nations' Agenda 2030 for Sustainable Development has broken this idea down into the specific targets of the 17 Sustainable Development Goals (SDGs), which deal with quality energy, livable cities, climate action, and social equity, among others [1], [11].

The decision-making process in sustainable development is very complicated by nature with many parties involved, opposite aims, uncertainty, and different data sources such as environmental sensors, satellite images, economic indicators, and social datasets [9]. Traditional decision support systems (DSS), which mainly rely on deterministic models and rule-based expert systems, find it hard to keep up with the data's highly dynamic and nonlinear characteristics [6].

Decision Support Systems first came into being to help human decision-makers via structured analysis and modeling. DSS's effectiveness, albeit, is mainly confined to well-defined contexts; traditional DSS are incapable of scaling up, changing, or learning [3] thus being quite a hassle in sustainability challenges. Nevertheless, the fusion of AI has given to the birth of AI-DSS or Artificial Intelligence-based Decision Support Systems that have increased predictive accuracy, adaptability, and scenario analysis [2], [9].

AI-DSS make possible the combination of forecasting, optimization, and adaptive decision-making through machine learning and advanced analytics. The systems are capable of analyzing considerable amounts of data, identifying new trends, performing scenarios simulations, and producing insights that are ready to act upon [2], [3]. The objective of this research paper is to provide a comprehensive review of AI-DSS in the context of sustainable development, introduce a conceptual framework, examine the various application domains, and elaborate on the challenges as well as future directions for research.

The principal goals of this paper are:

1. To review the present literature regarding AI-powered DSS in sustainability scenarios
2. To conceptualize a framework for sustainable decision making through AI.
3. Investigating crucial application areas in which AI-DSS assist in sustainable development
4. For discussion of challenges, issues, and research avenues

2. Related Work and Literature Review

Recent literature on AI-based Decision Support Systems (AI-DSS) for sustainable development can be broadly classified into methodological studies**,** domain-specific applications**,** and governance and ethical analyses**.** Unlike earlier reviews that mainly catalog applications, recent studies increasingly emphasize comparative performance, scalability, and policy relevance of AI-DSS.

Early DSS models were predominantly rule-based and deterministic, suitable for structured decision problems but inadequate for sustainability contexts characterized by uncertainty and high-dimensional data [3], [6]. Comparative studies consistently report that traditional DSS fail to capture nonlinear interactions among environmental, economic, and social variables, leading to suboptimal or static decisions [9].

Machine learning–enabled DSS significantly outperform classical DSS in predictive accuracy and adaptability. For instance, Liu et al. [9] demonstrate that ensemble-based AI-DSS achieve superior forecasting accuracy in environmental management compared to regression-based DSS. Similarly, Bibri and Krogstie [4] highlight that AI-driven urban DSS outperform GIS-only systems in handling real-time sensor data and multi-objective optimization.

Across application domains, methodological differences strongly influence outcomes. Supervised learning models dominate energy and agriculture applications due to the availability of labeled historical data [3], whereas reinforcement learning is more effective in dynamic environments such as smart grids and traffic systems [10]. However, most studies focus on single-domain optimization**,** neglecting cross-SDG interactions.

A critical gap identified across the literature is the weak integration between AI models and decision-making workflows**.** Many studies emphasize predictive accuracy but provide limited insight into how outputs translate into actionable policy decisions [12]. Furthermore, ethical concerns such as data bias, lack of explain ability, and uneven socio-economic impacts are often discussed conceptually but rarely operationalized within DSS architectures [6], [12].

Research Gaps Identified:

- Limited comparative evaluation of AI-DSS across multiple sustainability domains
- Insufficient integration of explainable AI within operational DSS
- Weak linkage between AI outputs and policy or governance mechanisms
- Lack of multi-objective frameworks addressing multiple SDGs simultaneously

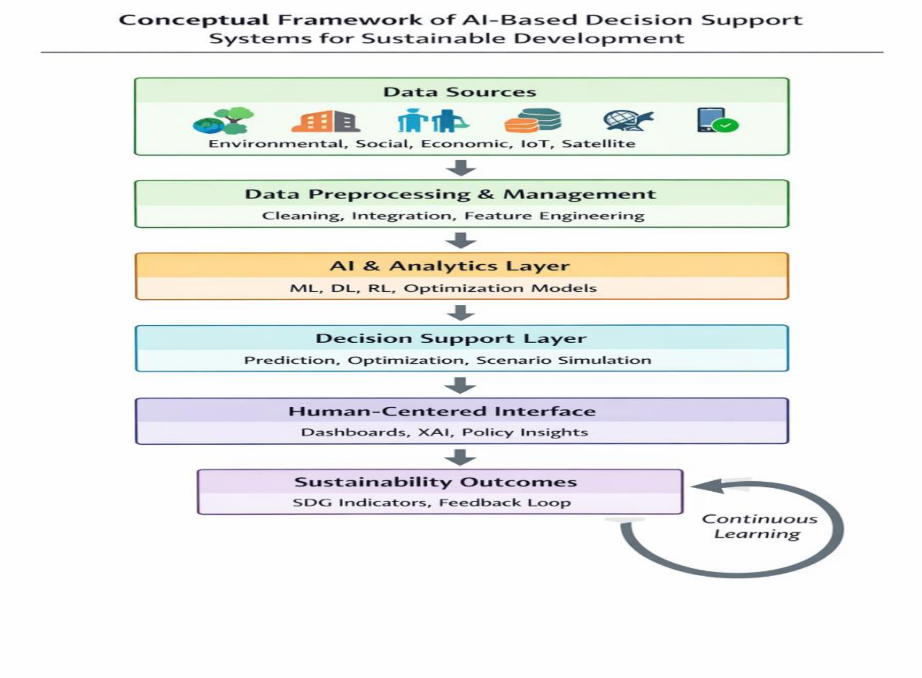
These gaps motivate the need for a clear conceptual AI-DSS framework that explicitly links data, intelligence, decision processes, and sustainability outcomes.

3. Conceptual Framework of AI-Based Decision Support Systems

3.1 Architecture of AI-Based DSS

To address the identified research gaps, this study proposes a layered AI-DSS framework that explicitly connects data acquisition, intelligence, decision logic, and sustainability outcomes.

Figure 1 illustrates the proposed AI-DSS conceptual framework, highlighting the end-to-end workflow from data collection to sustainability-oriented decision-making. Unlike conventional DSS models, this framework integrates continuous learning, explain ability, and feedback loops to support adaptive and transparent decisions aligned with SDGs.



This framework explicitly embeds explain ability, adaptability, and policy relevance**,** ensuring that AI-DSS outputs are not only accurate but also interpretable and actionable. The feedback loop enables continuous improvement as new sustainability data and policy outcomes become available.

3.2 Role of Machine Learning in Sustainable Decision-Making

One of the most important technologies behind the development of AI-DSS (artificial intelligence-based Decision Support Systems) is machine learning, which connects the traditional rule-based systems to data-driven adaptive intelligence. The learning aspect of machine learning enables the AI-DSS to discover complicated and non-linear patterns among environmental, economic and social factors that are usually hard to model with traditional statistical methods [3], [9]. By virtue of this strength, the systems can not only but also proactively manage the existing risks and the production of insights that are good for sustainable decision-making [9], [13].

Supervised learning is the most often used machine learning approach for sustainability-driven AI-DSS applications among various paradigms. Linear and nonlinear regression, decision trees, random forests, SVMs, and artificial neural networks, to name a few, are all used extensively for making predictions about energy and water demand, greenhouse gas emissions, soil and air pollution levels, crop yield, and so on [3], [9]. A typical example is the application of supervised learning in the field of renewable energy management. Here, models are applied that consider previous generations of data, meteorological conditions and power-line properties, all with the aim of predicting solar or wind power output, thus making the operations more efficient and less risky [10]. In the case of agriculture, such models are used to determine the amount of land needed for a particular crop, schedule watering, or even control pests, thus leading to better food security as a result of more precise resource allocation [9], [7].

On the other hand, unsupervised learning methods such as clustering, association rule mining, and dimensionality reduction are indispensable for exploratory data analysis. The application of these techniques allows the revelation of hidden patterns and innate structures in sustainability datasets that are complicated, such as the classification of regions with similar environmental risks, the division of consumers according to their energy consumption behavior, or the detection of emerging trends in biodiversity loss [3], [7]. Unsupervised learning, by uncovering such latent insights, not only facilitates but also increases the effectiveness of decision-making in the sectors of urban development, conservation, and public health [9], [4].

Reinforcement learning (RL) is a type of machine learning that further augments the capabilities of AI-DSS in sequential and dynamic decision-making scenarios. Through reinforcement learning algorithms, the systems get to interact with these highly complicated environments, and they keep learning the best policies by going through a process of trial and error while also considering multiple objectives such as economic efficiency, environmental impact, and social equity [10], [12]. Among such applications are smart grid energy dispatch, adaptive traffic signal control, dynamic water resource management, and long-term climate policy optimization. With the continuous evaluation of rewards and penalties, reinforcement learning gives the AI-DSS the ability to adapt its decision-making strategies in real-time, thus increasing the efficiency and resilience of the operations [10], [13].

The combination of supervised, unsupervised, and reinforcement learning in AI-DSS yields more powerful, flexible, and scalable decision tools that can effectively confront the different aspects of sustainable development. Predictive accuracy along with pattern discovery and dynamic optimization is what makes machine learning turn AI-DSS into intelligent systems which, in their turn, are capable of, and actually, supporting evidence-based, equitable, and environmentally responsible decisions [3], [9], [10], [13].

4. Application Areas of AI-Based Decision Support Systems for Sustainable Development

The application domains discussed below directly correspond to the layers and functionalities of the proposed AI-DSS framework (Figure 1). Each domain demonstrates how data-driven intelligence is transformed into operational decisions and measurable sustainability outcomes.

4.1 Sustainable Energy Systems

Within the proposed framework, energy-related AI-DSS primarily leverage the AI & Analytics and Decision Support layers to enable renewable energy forecasting, grid optimization, and emissions reduction. Reinforcement learning models dynamically adjust energy dispatch decisions based on real-time grid conditions, directly supporting SDG 7 (Affordable and Clean Energy) and SDG 13 (Climate Action) [10], [11].

Recent deployments in smart grids demonstrate that AI-DSS reduce energy losses by enabling predictive load balancing and storage optimization, outcomes unattainable through static DSS models [9], [10].

4.2 Sustainable Urban Planning and Smart Cities

AI-DSS uses traffic flows, mobility patterns, and sensor data for the analysis of traffic to decrease congestion and emissions as well as to support public transport planning and GIS-based urban development. Besides that, these systems are keeping track of air quality, noise pollution, and building energy consumption, therefore they are playing an important role in urban sustainability.

4.3 Agriculture, Food Security, and Environmental Monitoring

AI-DSS applications in agriculture are the area of precision farming, yield forecasting, irrigation optimization, and pest detection through computer vision which in turn leads to reduction in resource use and environmental impact. Besides, they help in the fight against climate change by supporting through disaster prediction, biodiversity monitoring, and ecosystem management with the help of satellite and IoT data.

5. Benefits of AI-Based DSS for Sustainability

The benefits of AI-based Decision Support Systems emerge from the synergistic interaction of framework layers**,** where predictive intelligence, optimization, and human-centered interfaces collectively enhance sustainability-oriented decisions.

5.1 Enhanced Decision-Making Quality

AI-DSS improve decision quality by transforming heterogeneous sustainability data into explainable insights through the AI & Analytics and Decision Support layers**.** Unlike traditional DSS, the proposed framework ensures that predictive accuracy is coupled with transparency, enabling informed and accountable decisions in energy planning, agriculture, and urban governance [3], [6].5.2 Resource Efficiency and Optimization

AI-DSS are a major factor in increasing resource efficiency because they make it possible to use energy, water, and land resources in the best way. In this case, the predictive modeling, real-time monitoring, and prescriptive analytics, the systems even indicate section of the inefficiency, propose the best resource distribution, and also go on to monitor the consumption activities to bring about the least waste [9], [10]. AI-DSS can take care of the situation in city planning through the management of traffic and the synchronization of public transport schedules, thus leading to the reduction of fuel consumption as well as greenhouse gas emissions. In addition, AI-DSS that directs precision irrigation systems in farms is able to use a lesser amount of water while still producing the same quantity of crops. Furthermore, AI-DSS in electricity networks are able to manage supply and demand smartly, enhance storage efficiency as well as cut transmission losses which result in both economic and environmental gains.

5.3 Adaptability and Real-Time Learning

AI-DSS are always adaptable in an integrated way, constantly drawing insights from new data to refine the significance and precision of their suggestions [9], [10]. This learning capability in real-time is especially useful in sustainability scenarios since the environmental, social, and economic conditions are very volatile. For instance, in climate risk management, AI-DSS can refresh their hazard forecasts using real-time inputs from satellites, weather stations, or sensors, thereby enabling quick reactions during floods, droughts, or hurricanes. Likewise, in the case of managing renewable energy, AI-DSS can be the driving force behind the grid's operations and pull down its impact on fluctuation in wind or solar generation - thus, resiliency and efficiency of operations will be increased.

5.4 Policy Evaluation and Scenario Simulation

AI-DSS aids the decision makers by providing them with models to assess the pros and cons of different policies and to visualize the long-term effects of the policies chosen before putting them in place [11], [12]. These systems by doing scenarios can predict the possible outcomes in terms of the environment, society, and economy thus giving the policymakers a chance to rely on evidence. Just to illustrate, in urban development, AI-DSS can predict the environmental and social impacts of a given infrastructure project and hence it will be easier to take decisions that will result in less pollution and a more livable area. In the energy sector, scenario analysis helps decision-makers to weigh the pros and cons of different renewable investments in terms of cost, output, and carbon footprint at the same time. The above-mentioned functionalities have the potential to decrease the level of uncertainty, help the organizations with planning, and make the creation of green policies easier.

6. Challenges and Ethical Considerations

AI-DSSs (AI-based Decision Support Systems) hold substantial prospects for enhancing sustainability, yet their application will face a range of challenges. The technical, ethical, social, and environmental issues brought about by these systems will have to be dealt with in a manner that will make the systems effective, trustworthy, and just. The acknowledgment of these problems is a prerequisite for responsible usage of the technology and for considering the sustainability of the future.

6.1 Data Quality and Availability

The quality and availability of the data are the main factors that influence the AI-based decision support systems (AI-DSS) most. In sustainability applications, the datasets generally have drawbacks such as incompleteness, inconsistency, and bias, which may lead to significantly lower model accuracy and reliability [6], [7]. To illustrate, sensor networks could lose certain data points because of malfunctioning devices, and historical accounts of farming or environmental practices might vary from place to place. Furthermore, the data gathered might be inadvertently revealing social or geographical discrimination, thus leading the AI to make biased suggestions that could adversely affect the already disadvantaged communities. To be able to tackle these issues, extensive validation, cleaning, augmentation, and integration of data from different sources is required.

6.2 Explain ability and Transparency

The majority of AI-based decision support systems (AI-DSS) rely on sophisticated "black-box" models, mainly deep neural networks and ensemble methods, plus, this leads to very confusing decision-making processes for the stakeholders [6], [12]. One aspect of the above-mentioned situation is that, the lack of transparency can have detrimental effects on trust and accountability, especially in the case of critical applications, for instance, disaster management, urban planning, or environmental policy. As a response to this challenge, several methods of explainable AI (XAI) like feature importance ranking, attention mechanisms, and post-hoc explanation techniques such as LIME and SHAP, have started to be applied more frequently. These methods not only enhance the level of interpretation but also the trust and interaction between human experts and AI systems, while being more efficient at the same time.

6.3 Ethical and Social Issues

When the system design and implementation are to the exclusion of certain groups, then AI-DSS could unintentionally reinforce the already existing disparities or isolate the weaker sectors of the population [5], [12]. Issues of privacy are raised, particularly in connection with the gathering of very sensitive information about people or locations on a large scale, which is similar to monitoring activities in smart cities or precision agriculture. Moreover, automation in the areas of energy management or farming may lead to the downsizing of the workforce, which would create social and ethical debates about fairness, retraining, and accessibility to technology for everyone. Establishing ethical governance frameworks, involving relevant stakeholders, and performing fairness audits to guarantee that the benefits of AI-DSS are equally shared are necessary measures to address these challenges.

6.4 Computational and Environmental Costs

The training of large-scale AI models demands a lot of computation and sometimes a heavy reliance on very high-performance, high-energy computers along with prolonged usage of GPUs/TPUs [10], [13]. The training of one large deep learning model alone, according to recent carbon studies, can produce the same amount of carbon as several cars during their entire lifetime which is an indication of the paradox in sustainability[10], [14]. The solutions that are meant to optimize resource usage and reduce pollution may turn out to be the main causes of carbon emissions, thus putting the very essence of sustainability in question.

One way to cope with this situation is to apply the green AI theoretical framework that aims at reducing the energy footprint through various tools that are not so much cutting down on the performance of models. The techniques like coiling down the model, pruning, and quantifying neural networks that are around 10,000, 100 or even a few tens of parameters will also facilitate quicker training and lower energy consumption as compared to the traditional two or three million parameters and so on [13], [15]. Energy-efficient hardware designs that include special AI accelerator chips will improve the performance-to-energy ratio of large-scale computations [14]. Furthermore, the use of cloud computing, edge computing, and federated learning enables distributed processing, thereby reducing the need for a central power-consuming infrastructure that is usually very high and at the same time offering the benefits of scalability, privacy, and responsiveness in real-time [10], [13]. All these measures combined allow the AI-DSS to retain its high predictive power and flexibility in the area of sustainability applications while reducing the environmental costs that result from computation.

6.5 Integration and Implementation Challenges

Apart from technical and ethical issues, the acceptance of AI-based Decision Support Systems (AI-DSS) in sustainability applications is frequently blocked by practical and organizational challenges [8], [12]. Most organizations show reluctance to change, as employees might not be ready to trust AI advice in place of conventional decision-making, or they might even be afraid of disturbance in their usual workflows. The shortage of end-user technical know-how makes the adoption process even more difficult, as the actors may not be aware of the full extent of the system's outputs or how to effectively use the AI-DSS tools [12].

Regulatory and legal limitations can also be a reason for slow deployment, particularly when AI-DSS make use of sensitive environmental, personal, or location-based data. Adherence to the data protection laws, the regulations of the specific industry and the organizational governance policies demands meticulous planning and supervision [5], [12]. Usually, the integration of AI-DSS into existing workflows, governance structures or policy frameworks requires plenty of coordination, with the involvement of IT teams, domain experts, policy-makers and management in order to make sure that the systems are in line with the company's objectives and decision-making approaches [8], [12].

Participatory co-design methods are suggested to do away with these obstacles whereby the end-users, domain experts and the developers together design the AI-DSS tools which then become very usable, relevant and accepted [12],[15]. Rather, a capacity-building program entailing training sessions, workshops, and continuous support among others can improve the stakeholders' comprehension and facilitate their good use of the AI-DSS outputs [8]. Moreover, synchronous deployment of AI-DSS with the regulatory frameworks and the industry standards not only guarantees legal compliance but also builds trust between stakeholders [5], [12]. Collectively these actions may result in a smoother adoption of AI-DSS,

7. Future Research Directions

Future research should focus on:

- Explainable and interpretable AI models for sustainability
- Integration of AI-DSS with policy and governance frameworks
- Development of energy-efficient and green AI techniques
- Multi-objective DSS addressing multiple SDGs simultaneously
- Participatory AI-DSS involving stakeholders in decision-making

8. Conclusion

The AIded Decision Support Systems (AI-DSS) provided with an AI component are a great advantage for the ecosystem, since they will allow the implementation of adaptive, data-driven, and evidence-based decision-making easily and quickly in all areas like energy, agriculture, urban planning, and environment management [9]. Apart from these, machine learning, predictive analytics, and real-time data integration are majorly the technologies that support such systems in efficiently allocating resources, giving better policy evaluation, and building resilience through overcoming environmental and socio-economic uncertainties. The implementation of AI-DSS has its pros, but it also carries significant challenges along with it, like poor data quality and no availability, lack of transparency in black-box models, ethical and social implications, and organizational or governance constraints [6], [7], [12]. Acknowledging that these hardships exist, one possible suggestion is to resort to explainable AI methods for ensuring the better interpretability of the model, setting up responsible governance systems to secure fairness and equity, and promoting interdisciplinary collaboration among researchers, policymakers, and practitioners [1], [11], [12]. Effective handling of these problems is critical for reaping the full benefits of AI-DSS for the attainment of global sustainability targets to be reached by 2030, as laid out in the UN 2030 Agenda.

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