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A HYBRID ARTIFICIAL INTELLIGENCE FRAMEWORK FOR SUSTAINABLE DEVELOPMENT DECISION SUPPORT

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ABSTRACT

As environmental challenges get worse, we need tools that assist us make informed, flexible, and unambiguous decisions. A lot of people are starting to believe that AI could be a great assist in reaching the SDGs (Sustainable Development Goals). On the other hand, a new study shows that some policies, how they are carried out, and not combining policies are negative for the environment. This article analyzes recent studies on AI-driven systems for decision-making in sustainable development, focusing on machine learning, fuzzy systems, multi-criteria decision-making (MCDM), evolutionary optimization, and hybrid intelligent architectures. This study contends that singular AI methodologies are inherently inadequate for addressing multi-objective sustainability trade-offs characterized by uncertainty, data heterogeneity, and ethical constraints, as demonstrated by a comparative analysis of seminal publications from 2015 to 2024. The evaluation uncovers issues with concepts and methodologies, particularly for explainability, compliance with governance, and scalability to other domains. One way to solve this challenge is to utilize a layered hybrid AI system with parts for open governance, predictive modeling, figuring out what to do when you don't know what to do, and optimization algorithms. The study shows that future systems for making decisions that are good for the environment shouldn't only use predictive algorithms. They should employ hybrid frameworks that operate well with technology and are good for people and the environment.

1. INTRODUCTION

In the past, people wanted employment that would help them improve. But now it's a problem that needs a lot of thought to solve. The UN's Sustainable Development Goals (SDGs) have a lot of diverse goals. For example, they want to help the economy grow, make the world a better place to live, and make society more equitable. But it's still hard to reach these goals because there are too many laws that change all the time, not enough information, and goals that don't match up.

Many people think that AI can help make changes that last. Russell and Norvig (2016) say that many people think AI is only computers that can think for themselves. AI systems have demonstrated proficiency in data management. For example, they can predict the weather, make smart grids better, and count different kinds of animals (Rolnick et al., 2019; Goodfellow et al., 2016). The investigation reveals systemic issues, including ambiguous algorithms, insufficient emphasis on certain domains, and non-compliance with governance frameworks (Vinuesa et al., 2020; Floridi et al., 2018).

A thorough analysis of recent PhD dissertations and published literature reveals that sustainable AI research mostly prioritizes problem-solving over architectural considerations. Models are designed to produce a variety of predictions, irrespective of their coherence with the broader context. This paper asserts that reductionist methodologies are insufficient for decision-making in sustainable development, as they neglect multi-objective optimization, uncertainty analysis, interpretability, and ethical accountability.

There are three key purposes for the review:
- To give a full list of all the AI methods used in research on sustainable development.
- To compare what people are saying now about hybrid intelligent systems to what they have stated in the past.
- To create a hypothetical hybrid AI system that can make decisions that last.

2. LITERATURE ANALYSIS

2.1 Artificial Intelligence in Sustainable Development:

Vinuesa et al. (2020) did a lot of study on how AI affects all of the Sustainable Development Goals (SDGs). They discovered 134 positive aspects and 59 negative aspects. Their study offers significant insights into the broader context; nonetheless, it primarily addresses subjects rather than methodically organizing them. They don't learn how to put things together, so they don't get anything out of it.

Rolnick et al. (2019) also talked on how machine learning could help battle climate change, especially when it comes to figuring out how much carbon there is and how much energy people will use. People want to know if the technology works, not if it can help them decide.

Meseguer-Ruiz et al. (2023) contend that AI must progress from rudimentary predictions to extensive, long-term governance. Their research encompasses ethical and regulatory dimensions, alongside the findings of Floridi et al. (2018), which underscore the significance of accountability and transparency in the utilization of AI. Nonetheless, research focused on governance fails to yield a conclusive hybrid design.
The research articulates a conceptual differentiation: robust evidence of AI's potential juxtaposed with insufficient institutional integration for policy-oriented sustainability decision-making frameworks.

2.2 Machine Learning Dominance and Its Structural Limitations

The best approach to learn how to make things last is through machine learning. Deep neural networks, convolutional neural networks (CNNs), and recurrent models like long short-term memory (LSTM) networks are often used to predict the weather (Reichstein et al., 2019), crop yields (Kamilaris & Prenafeta-Boldú, 2018), and renewable energy (Liu et al., 2021).

A lot of people don't know how to use these strategies, but they work well for making predictions (Doshi-Velez & Kim, 2017). People who decide what is sustainable want to know exactly why they do what they do, not just a general idea of how likely it is to work.

Machine learning algorithms also need data to work. Because new enterprises don't know much about sustainability, they make sure their ideas are right (Kumar et al., 2022). AI-powered technology can't help the environment all around the world because the data is different in each region.

We can use machine learning to make predictions, but it can't help us cope with uncertainty, understand policy, or figure out how to reach two goals that are at odds with each other.

Table 1: Comparative Analysis of AI Techniques in Sustainable Development

Technique	Strength	Use Area	Limitation	Gap
Deep Learning	High accuracy	Climate, agriculture	Black-box	Low explainability
Random Forest	Robust classification	Waste management	Weak temporal modeling	Limited optimization
Fuzzy Logic	Handles uncertainty	Supplier evaluation	Static rules	No adaptive learning
AHP / MCDM	Structured ranking	Smart cities	Subjective weights	No dynamic update
Genetic Algorithms	Multi-objective	Energy allocation	High computation	No governance reasoning

2.3 Multi-Criteria Decision Systems and Uncertainty Modeling

2.3.1 Analytical Hierarchy Process and MCDM

Saaty's (1980) Analytic Hierarchy Process (AHP) is crucial for the assessment of sustainability evaluations. Numerous PhD dissertations employ AHP and TOPSIS to identify environmentally sustainable suppliers, evaluate renewable initiatives, and appraise smart cities (Govindan et al., 2016).

The core principle of MCDM methodologies remains constant. Sustainability indexes can alter, but experts always look at how bad each situation is. Fuzzy extensions (Zadeh, 1965; Kahraman et al., 2015) can help you understand concepts better, but they can't learn new things.

Machine learning methods are harder to understand than MCDM, but MCDM is easier to change. This trade-off emphasizes how crucial it is to change things around.

2.3.2 Evolutionary and Multi-Objective Optimization

Deb's (2001) multi-objective evolutionary algorithms (MOEAs) showed that computers may work on two different goals at the same time. Researchers frequently utilize MOEAs to oversee water resources (Reed et al., 2013) and to assess the extent of renewable energy usage (Zhang et al., 2020).

These steps assist make sure that the economy, technology, and the environment all work together. But optimization approaches rely heavily on established goal functions, thus they can't take into account new things that affect sustainability.

So, even if optimization can make things work better, it doesn't imply you'll always know how to use things or learn from your failures.

Table 2: Evolution of AI in Sustainability Research

Period	Dominant Method	Characteristic	Limitation
2010–2014	Statistical + MCDM	Structured analysis	No learning capability
2015–2018	Machine Learning	Predictive focus	Black-box models
2019–2021	Deep Learning + IoT	Real-time monitoring	Fragmented systems
2022–2025	Hybrid AI + XAI	Integrated support	No unified architecture

2.4. Hybrid Artificial Intelligence: Comparative Synthesis

Hybrid AI uses a specific kind of computer to solve problems in a lot of different fields.

2.4.1 Neuro-Fuzzy Architectures

Neuro-fuzzy systems combine adaptable neural networks with fuzzy inference methods. Jang (1993) showed that they worked well for simulating nonlinear systems. Researchers looking into sustainability can use neuro-fuzzy algorithms to find out how much energy they need and how clean the water is (Shamshirband et al., 2019).

Neuro-fuzzy models are simpler to grasp than neural networks alone. But they only work in one place, and it takes a lot of energy to get them to work.

2.4.2 Machine Learning + Optimization Hybrids

Recent research has combined evolutionary optimization with machine learning models that can provide predictions (Sun et al., 2022). To start, these mechanisms determine how long something will survive. They then change the rules so that it lasts longer. You could assume you know what will happen with this two-step process, but it doesn't always teach you how to operate a business or what's right and wrong. Some of these models also don't contain the parts that help people learn about AI (XAI).

2.4.3 AI Governance and Explainability

Explainable AI has arisen as a remedy for algorithms that are challenging to understand (Ribeiro et al., 2016; Gunning & Aha, 2019). In sustainable ecosystems, explainability includes both technological and political factors, since choices affect people, resource distribution, and fairness in the environment.

Many people are talking about it, but AI researchers that care about the environment still haven't done much to make things clearer. Some PhD theses use SHAP, LIME, or rule-based explanation systems to develop decision support systems that last.

This indicates that the study is not very excellent.

Table 3: Identified Research Gaps in Existing Hybrid AI Studies

Dimension	Current Status	Deficiency	Required Advancement
Architecture	Domain-specific models	No unified framework	Layered hybrid design
Explainability	Optional add-on	Not embedded structurally	Built-in governance layer
Policy Alignment	Weak integration	Output not policy-driven	Rule-based engine
Scalability	Local systems	Limited cross-sector use	Modular cloud framework

2.5. Synthesis of Research Gaps

A survey of the literature identifies four primary issues:

Architectural Fragmentation: Numerous studies indicate that AI solutions do not need to reside within the same system to facilitate decision-making.

- Not being able to explain: The Sustainability DSS isn't using XAI technology to its full potential.
- Disconnect in Governance: The AI knows what the policy says, but it doesn't always follow it.
- Issues with cross-domain scalability: A lot of hybrid solutions only work in one area.

One major issue is that there is no single hybrid framework capable of performing all of these functions in both theoretical and practical contexts: prediction, reasoning, optimization, and governance.

3. CONCEPTUAL HYBRID AI FRAMEWORK FOR SUSTAINABLE DEVELOPMENT DECISION SUPPORT

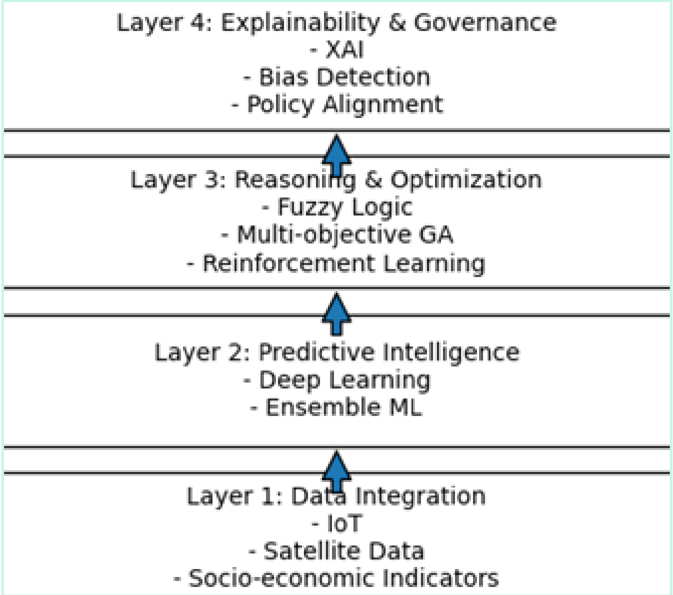
This review suggests a four-part plan that involves working together:

Layer 1: Make sure everything fits and makes sense.
Getting data from a variety of various places, like the Internet of Things (IoT), satellite photos, legal databases, and economic data.
Step Two: Choosing the Right Things
Looking for new ways to teach people about ensemble models and deep learning.

Level 2: Making things and ideas better
We employ fuzzy logic to help us understand things that aren't clear. We employ evolutionary algorithms to help us choose between distinct aims. Reinforcement learning helps us get better at what we do over time.

Layer 3: Putting things in order and figuring them out
XAI modules, tools for finding bias, engines that make sure rules function together, and dashboards that keep track of how things are progressing. This plan makes ethical governance the most important part of the firm, which is different from earlier research that thought it was a little concern.

Fig. 1: Layered Hybrid AI Framework for Sustainable Development Decision Support



4. DISCUSSION

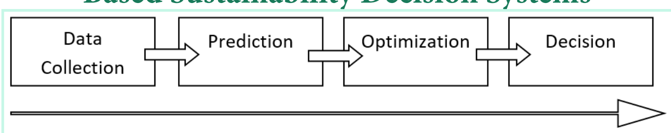
A lot of people are using AI tools that work for both robots and people. We are moving away from using predictive analytics and toward long-term governance that works for everyone. We need to learn these things before we can achieve anything else:

- Making sure everything is right
- The cost of computers
- People who don't want to do it

Not knowing the regulations. Some new ideas that could help with some of these difficulties are federated learning (Yang et al., 2019), digital twins for sustainable cities (Batty, 2018), and Green AI principles (Schwartz et al., 2020).

Cross-sector pilot studies are essential for upcoming doctoral research as they assess the efficacy of hybrid solutions in practical applications.

Fig. 2. Adaptive Feedback Cycle in Hybrid AI-Based Sustainability Decision Systems



5. CONCLUSION

The report says that AI might help keep society, the economy, and the environment stable. You can't only utilize optimization methods, MCDM, or machine learning to make judgments that are good for the environment and do more than one thing. Most of the time, these methods don't work with other people since they don't know the rules or don't follow them. This study shows that AI systems need predictive analytics, models for dealing with uncertainty, optimization algorithms, and explicit instructions on how to use them. The suggested layered structure sees sustainable decision support as a dynamic system that changes and interacts with other systems throughout time, not just as a way to make predictions.

We need to see if AI is right and works well in the actual world, where there are a lot of people. Hybrid AI is a big step toward making it easier and more moral to come up with ways to protect the Earth.

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