

IRCAI

Scientific excellence, global public dialogue and technology for sustainability, inclusion and equality.

Responsible AIoT and TinyML

School on Applied AI for Sustainable Development | (smr 4210)
Trieste 24.3.2025



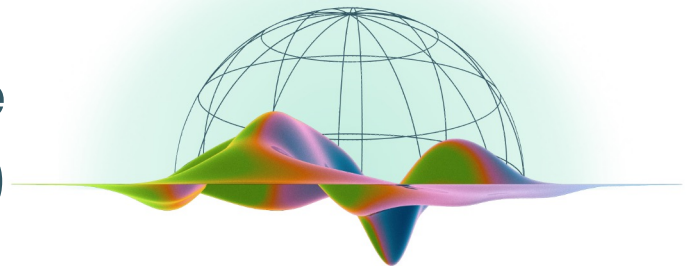
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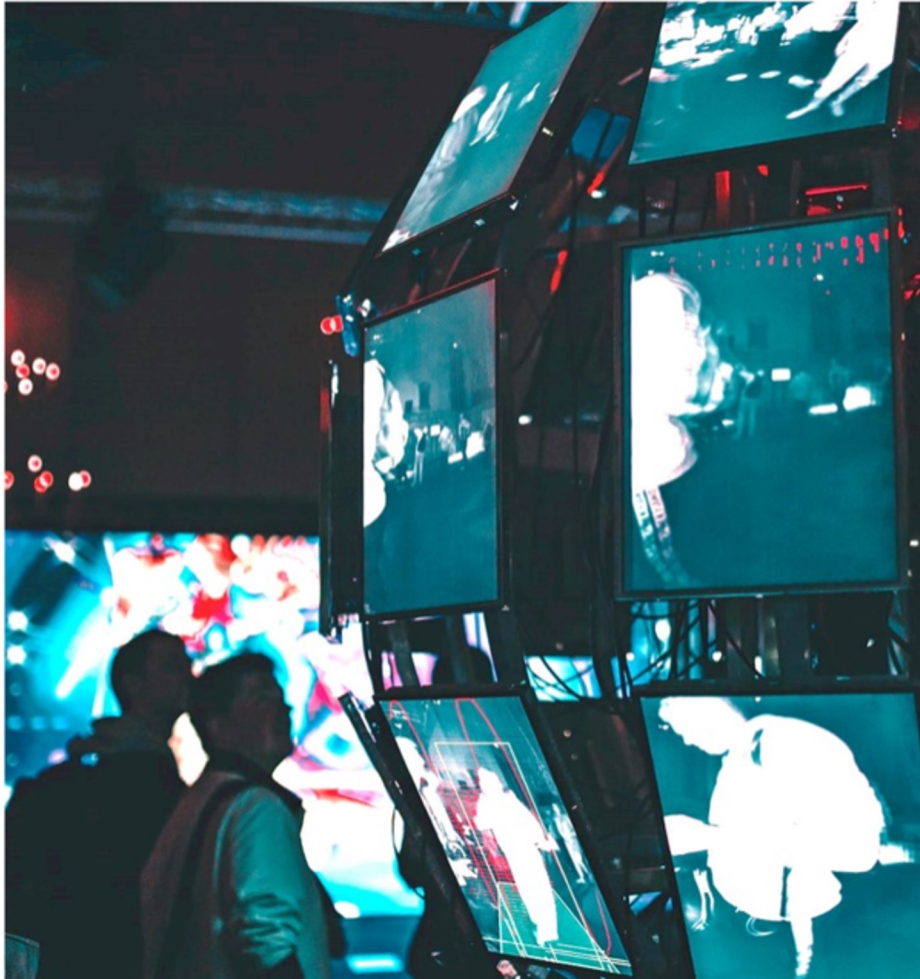


Recommendation on the Ethics of AI

- After extensive consultations, recommendation adopted at the UNESCO assembly in November 2021
- Human centered: how can individual humans be protected from misuse and enriched by the use of AI
- Closely aligned with European humanistic values and with EU initiatives as well as Council of Europe

Global Forum on the Ethics of AI (GFEAI)





Potential for new and old threats being enhanced

- Citizen control as envisaged in Brave New World
- Automatic processing of decisions that ignore marginalised groups
- Automatic weapons that can be used to disable legitimate protest or wage destructive wars

GLOBAL CONFERENCE ON AI AND HUMAN RIGHTS

13 and 14 June 2024
Faculty of Law,
University of Ljubljana (Slovenia)



www.ai-right-to-life.si



unesco

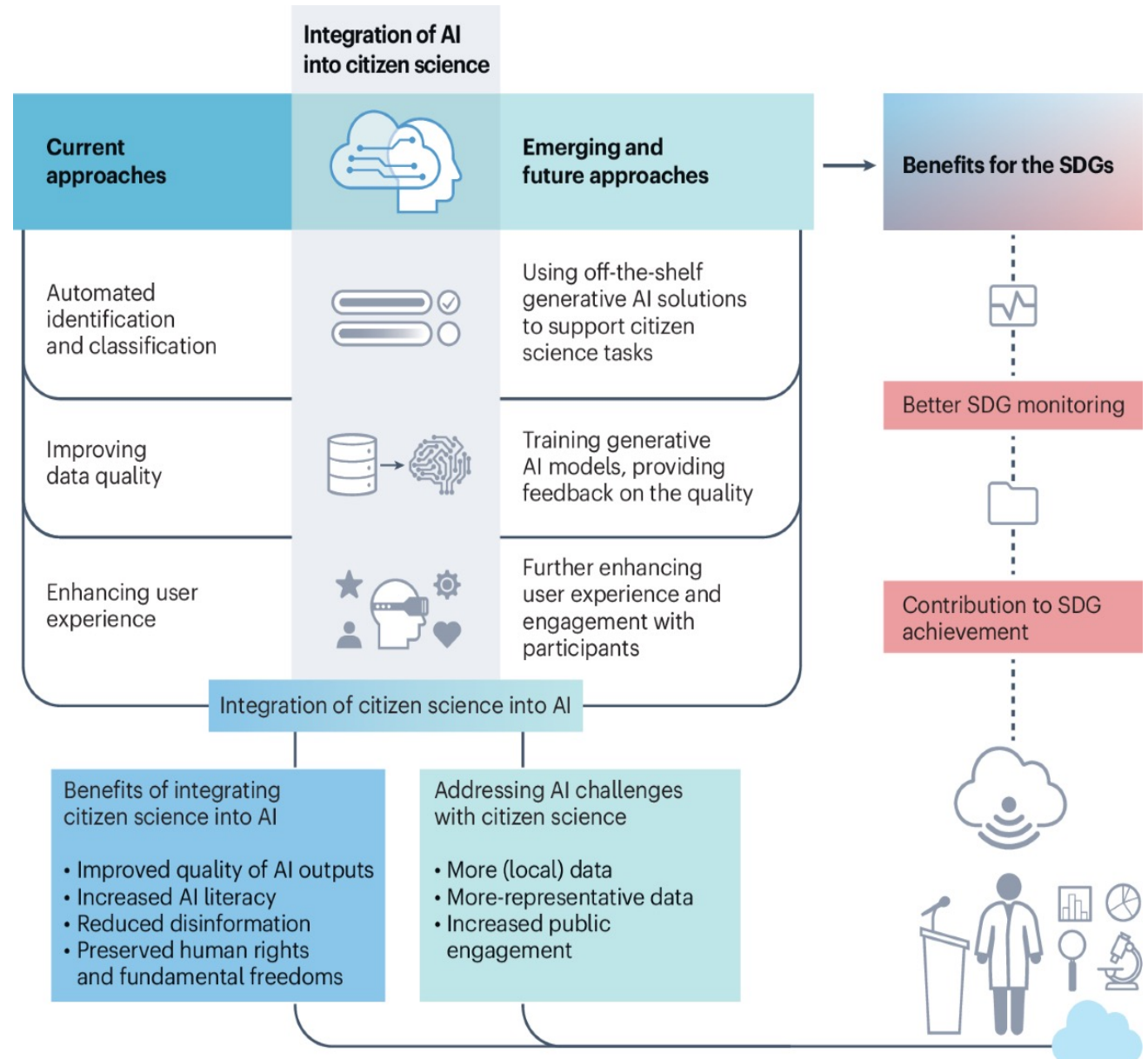


- EU AI Act is first attempt, but risk based so that many systems not covered
- One advantage of the UNESCO recommendation is that it is vague: forcing designers to think through unforeseen consequences:
 - assessing when human rights have been compromised, system acted unfairly, introduced bias, etc.
 - Any formal definition will inevitably be limited and motivate circumvention

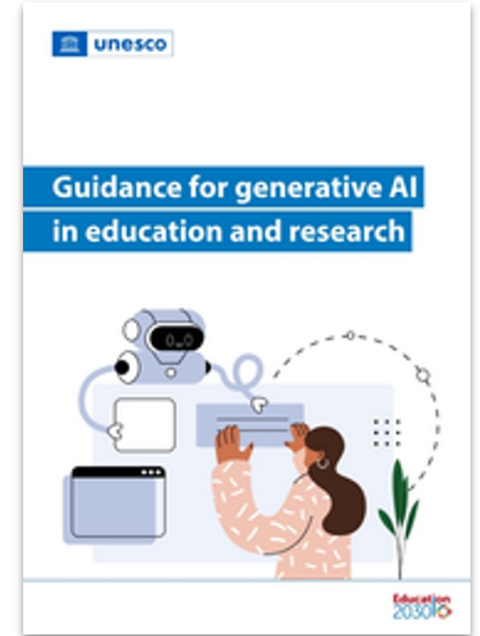




<https://unesdoc.unesco.org/ark:/48223/pf0000385082>



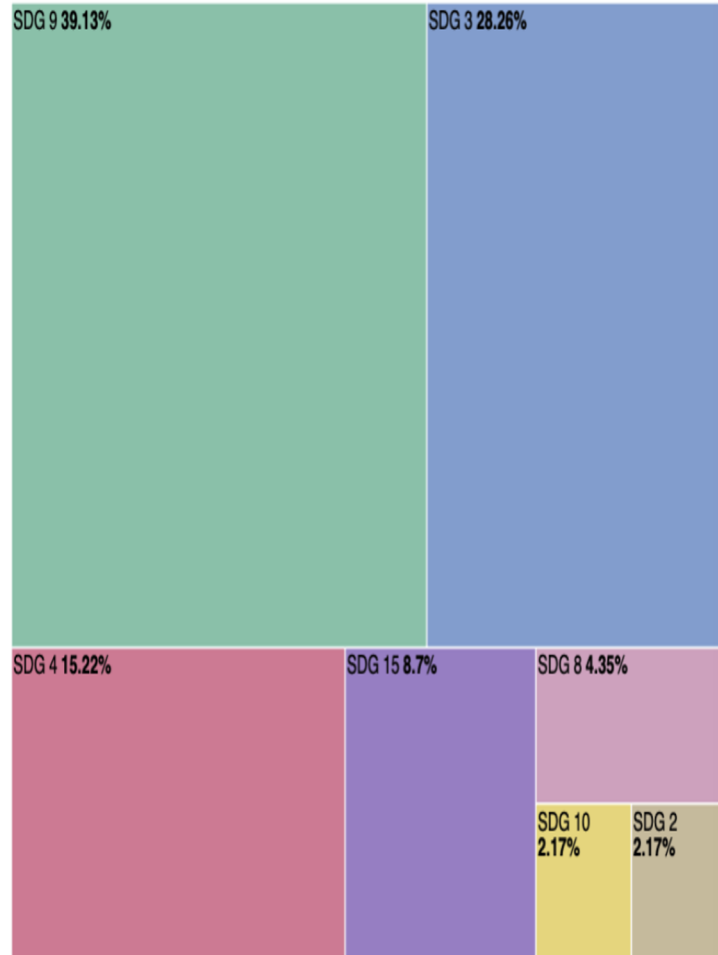
Leveraging the collaborative power of AI and citizen science for sustainable development, Nature Sustainability 2024



One way to try to offset the potential misuse is to regulate greater disclosure

- AI should be educational, broadening our understanding of situations and content
- This could be a requirement that enables users to make up their own minds
- Many of the manipulations rely on suggesting that full disclosure is not available

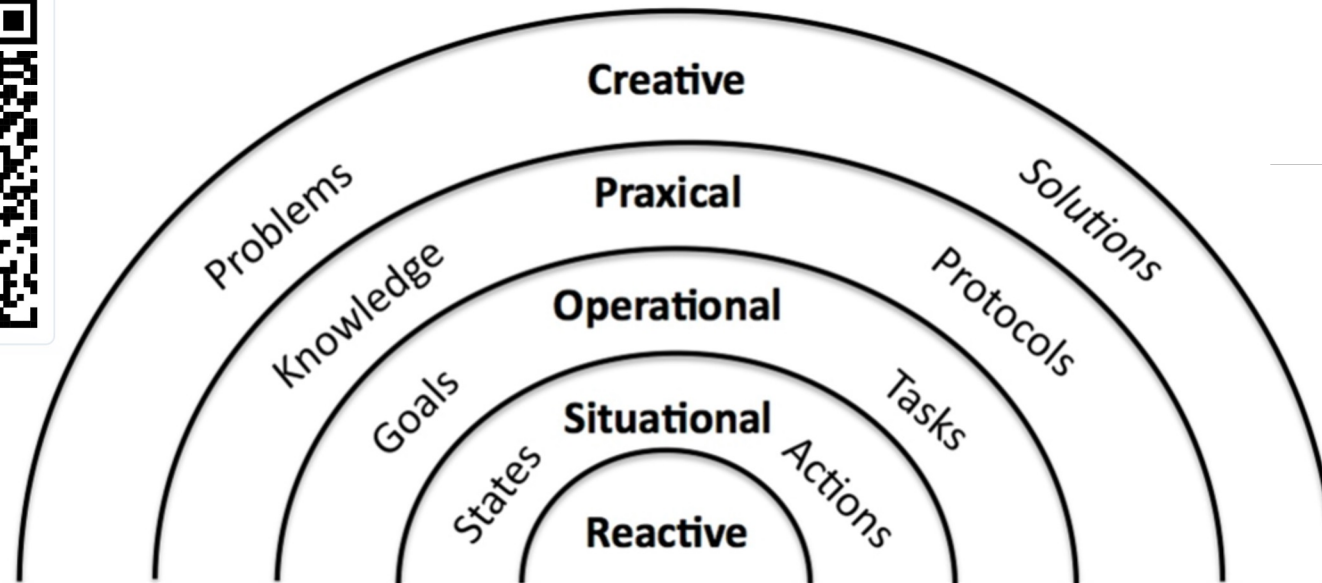
OPERATIONALIZED ETHICAL AND FUNCTIONAL DIMENSIONS WITH PRIORITY AREAS FOR TINYML AND STEAM EDUCATION



Dimension	Description	EdgeAI/TinyML	STEAM Education
Transparency	Clearly communicate AI operations, data handling, and inference logic to participants to build trust and accountability in both community science and educational contexts.	High – enables interpretability of local models and data flows.	High – critical for teaching explainability and responsible AI use.
Inclusivity	Ensure equitable access to AI tools, datasets, and learning resources, addressing disparities in infrastructure, gender representation, and cultural participation.	Medium – supports broader participation in device deployment.	High – foundational for equitable AI literacy and engagement.
Fairness	Identify and mitigate algorithmic bias across data collection, labeling, and model evaluation processes, especially in community or low-resource settings.	High – essential for localized and context-aware model training.	High – core concept for teaching ethical reasoning in AI and data science.
Environmental Responsibility	Assess and reduce lifecycle impacts of AI hardware, including sourcing, energy consumption, and end-of-life management.	High – TinyML’s edge devices directly affect ecological sustainability.	Medium – integrated into STEAM through sustainability modules and project design.
Cultural Diversity	Incorporate local knowledge, indigenous epistemologies, and linguistic diversity into AI datasets, interpretations, and learning activities.	Medium – supports culturally relevant sensor deployment and data interpretation.	High – encourages interdisciplinary, culturally responsive pedagogy.
Operational Assistance	TinyML devices perform localized inference for environmental monitoring, health tracking, or IoT sensing, reducing reliance on cloud infrastructure.	High – primary operational focus of edge ML systems.	Medium – serves as an applied learning example in engineering and computing courses.
Decision Support	Generative AI systems synthesize data insights and summaries to assist collective decision-making and policy formation in citizen science projects.	Medium – complements TinyML data with higher-level synthesis.	High – enhances inquiry-based learning, problem-solving, and critical reflection.
Interpretive / Narrative Collaboration	AI systems co-generate visualizations, reports, and educational materials with human collaborators, promoting reflective learning and knowledge co-creation.	Medium – relevant in projects using embedded visualization or reporting tools.	High – central to creative and narrative integration in STEAM curricula.



- Human-centric AI is at the centre of the European vision of a positive role for AI
- AI that empowers humans to be more effective, more creative, more understanding
- Human-centric AI (HCAI) has been the focus of the Humane AI Network of Excellence
- How does its research agenda envisage HCAI?



Common Ground through Explanation, Instruction, Demonstration, Experience

Humane AI Research agenda highlights the ingredients of Collaborative Intelligent Systems:

- Need to find ‘common ground’ across a range of levels in order to enable effective cooperation/communication
- Levels identified roughly correspond to different styles of collaboration with collaborative systems potentially involving more than one level

HumanE AI Net: The HumanE AI Network

Grant Agreement Number: 952026
Project Acronym: HumanE AI Net

Project Dates: 2020-09-01 to 2023-08-31
Project Duration: 36 months

D6.1 Strategic Research Agenda

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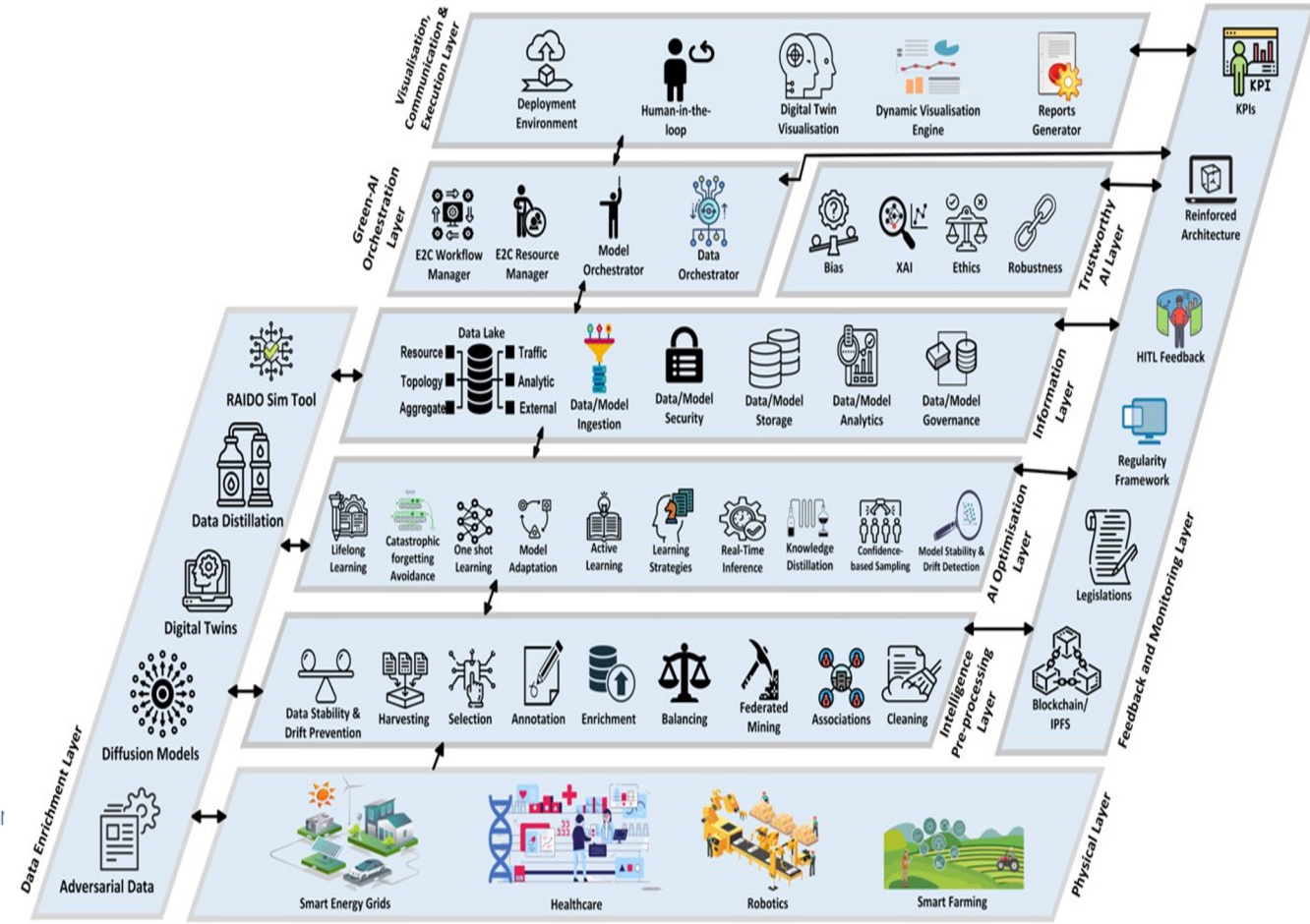
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RAIDO

raido-project.eu

Reliable AI and Data Optimization

An integrated platform for Green and Energy-efficient data and model related operation



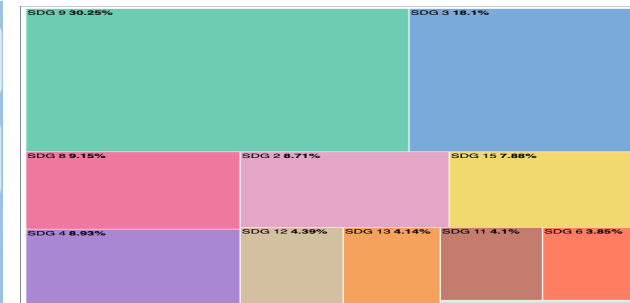
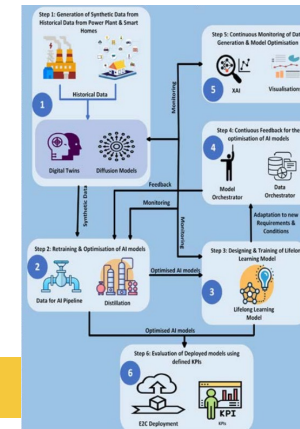
Green AI Orchestration Bridging Trustworthy AI and Edge AI through tinyML for Frugal Intelligence

Joao Pita Costa^{a,*}, Marco Zennaro^b, Ioana Ntinou^{c,1}, John Shawe-Taylor^a

^aInternational Research Centre on AI under the auspices of UNESCO, Jamova cesta 39, Ljubljana, 1000, Slovenia

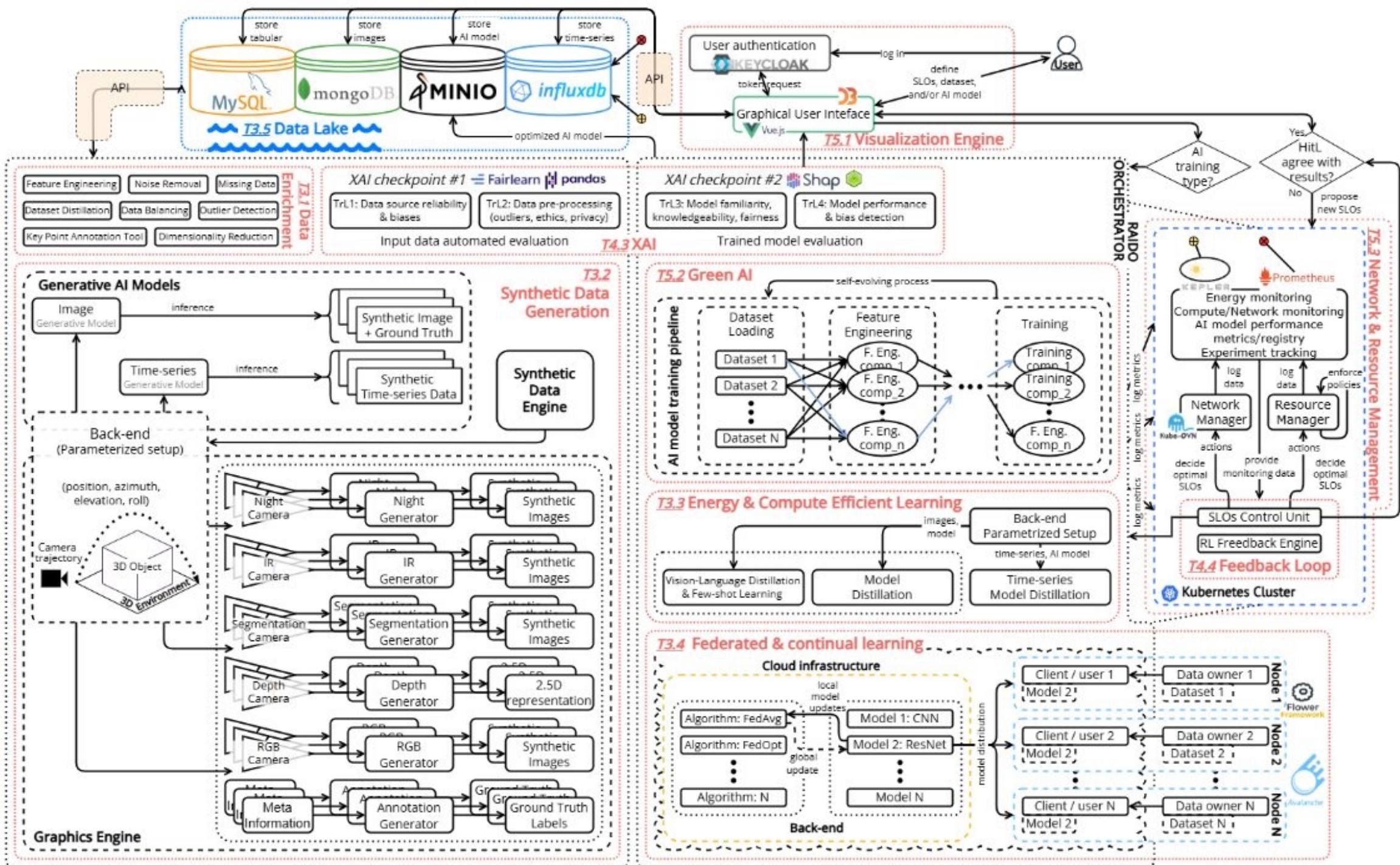
^bICTP, Str. Costiera 11, Trieste, 34151, Italy

^cQueen Mary University of London, Mile End Road, London, E1 4NS, UK

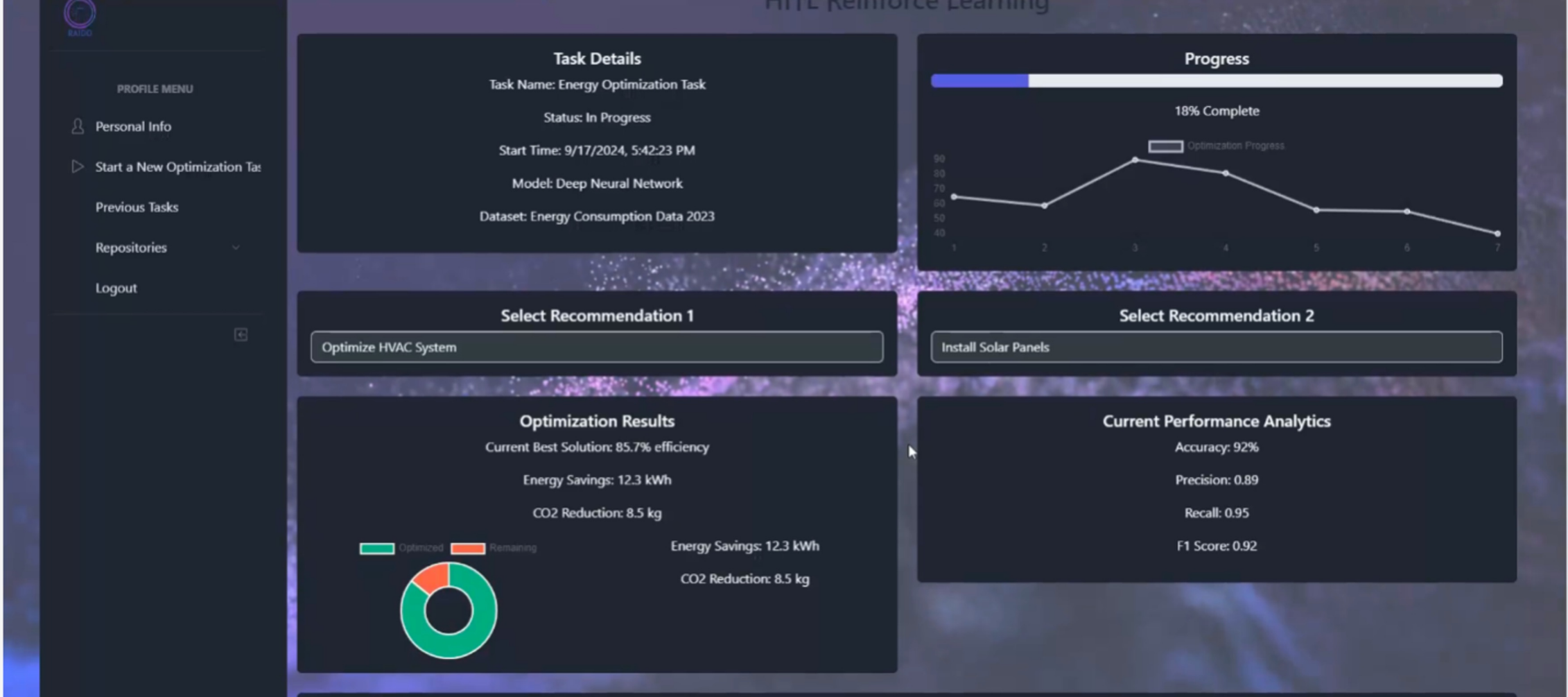


Workshops & Networking





RAIDO AI Optimisation Platform



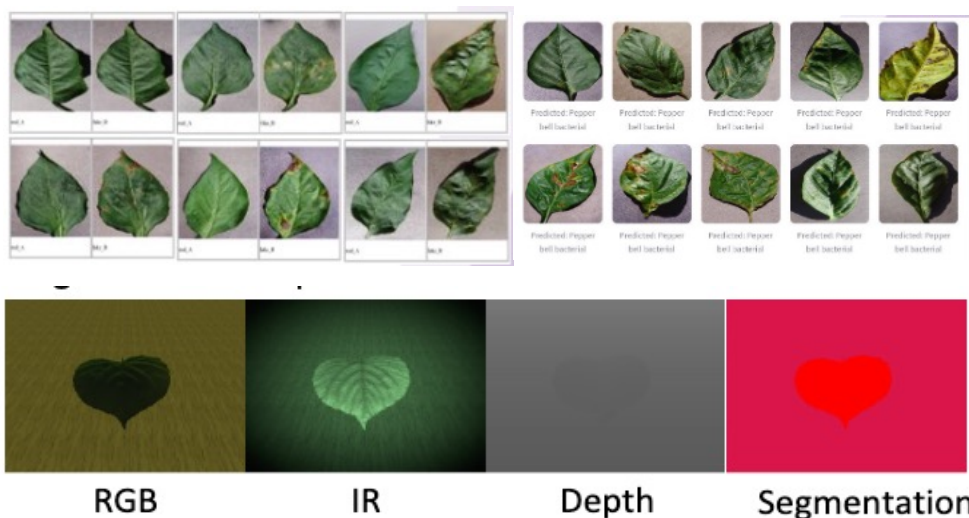


RAIDO Data Enrichment and Distillation Software (DEDS)



Powering Ethical AI with Smarter Data, Lower Costs, and Seamless Compliance

DEDS helps organisations that develop and deploy AI solutions that struggle with unpredictable costs, technical complexity and ethical compliance by employing **optimised data flows** and providing **quality synthetic data**, while enhancing competitive positioning, enabling continuous compliance and automate workflows with built-in ethical AI capabilities.



Components:

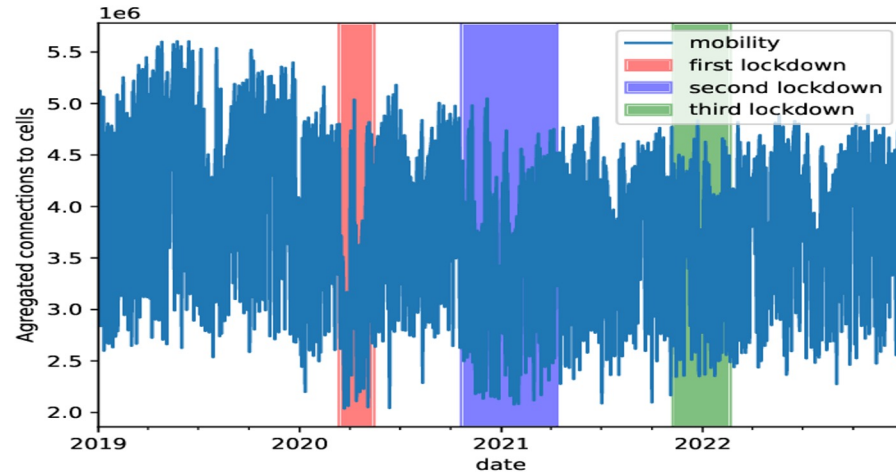
- Data Enrichment (MINDS)
- DataSim (KU)
- Data Lakes (UBI)



RAIDO Toolbox for Optimized and Energy Efficient Training of DL Models

Making AI training sustainable through model distillation and efficient data handling

The toolbox for optimized and energy efficient training of DL models helps AI researchers (Post Docs in AI institutions) who want to train an AI model by **avoiding using a high number of GPUs** and enable availability of models, technologies for distillation and data loading.



Components:

- Distill-ai
- Lifelong Learning in Federated Architectures

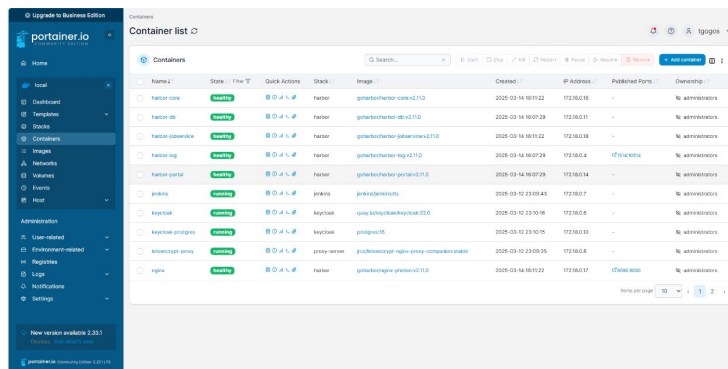


RAIDO Transparent and verifiable NFTs for AI model cards using Blockchain Smart-Contracts



Ensuring AI model accountability with verifiable and tamper-proof NFTs

Transparent and verifiable NFTs for AI model cards using Blockchain Smart-Contracts help organisations and consortia involved in responsible AI development, auditing, and compliance that struggle with the complexity and costs associated to tracking ethics and AI governance compliance to track and verify an AI model's lifecycle using NFTs to **mitigate unauthorised model alterations** and **simplify audit processes**, while achieving a **high level of trust and transparency** ensuring compliance with current and future regulation with cryptographic proof guaranteeing traceability and accountability of AI model governance.



Component:

- RAIDO Blockchain

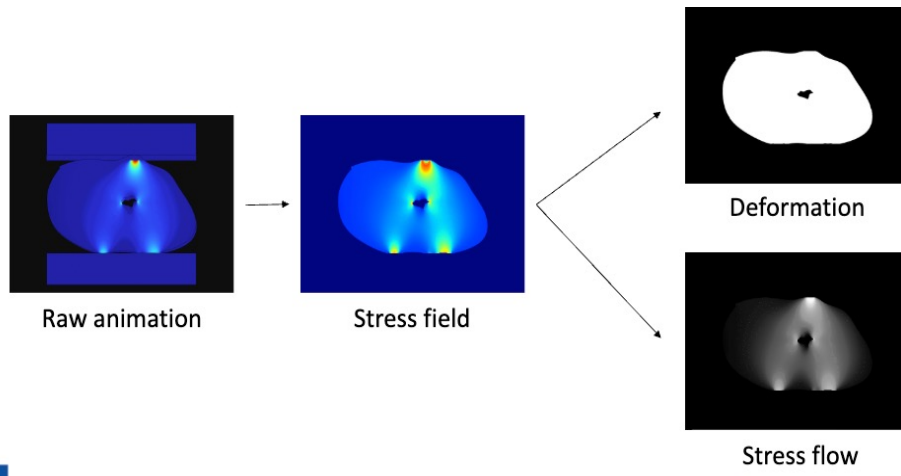


RAIDO Human-in-the-loop interface of explainable AI optimization platforms



Versatile, explainable AI to optimise farm operations with confidence

The human-in-the-loop interface of explainable AI optimisation platforms helps companies working in farm management which want to customise business AI models (in terms of energy, efficiency, accuracy and speed) with given customer priorities by **reducing lack of model versatility** across use cases and **enabling quicker and better-informed decisions** about all aspects of farm management.



Components:

- XAI engine & framework
- Multi-objective Reinforced Benchmarking
- Visualisation Tool



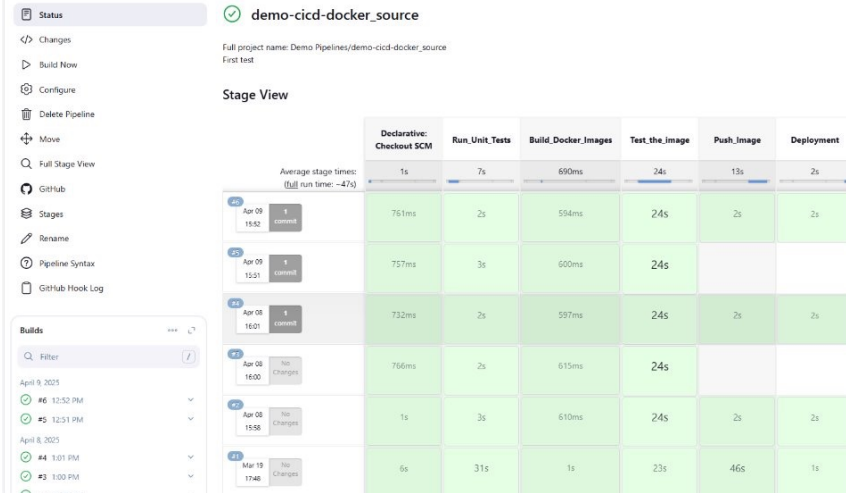


RAIDO RAIDO Green-AI Orchestrator



Seamless orchestration of legacy and modern AI tools for greener workflows

RAIDO Green-AI Orchestrator helps AI developers who want to monitor hardware/software resources by reducing difficulty integrating new AI tools with legacy systems or dashboards and enabling **tangible energy and cost savings** from efficient AI workflows



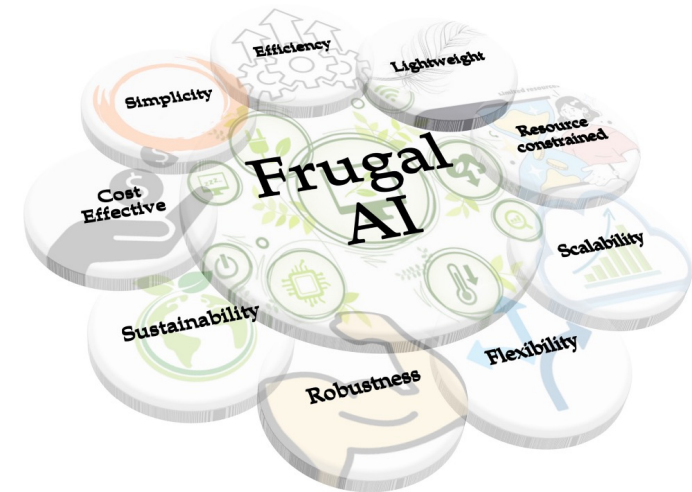
Components:

- Data Lakes
- E2C continuum resource allocation and network management
- Self-evolving Green-AI and Data Orchestration

RAIDO & Frugal Edge AI

Frugal Edge AI intersects with several contemporary research trajectories, notably Edge Intelligence, Green AI, and Sustainable Computing.

- **Edge Intelligence** has emerged as a response to the latency, privacy, and bandwidth limitations of cloud-based AI systems, focusing on distributing computation closer to data sources
 - **Green AI** advocates for efficiency and transparency in resource use throughout the AI lifecycle,
 - **Sustainable Computing** emphasizes energy-aware system design
- Frugal Edge AI synthesizes these streams by prioritizing algorithmic compactness and energy efficiency through techniques such as model pruning, quantization, and on-device learning, as exemplified in the field of TinyML. Unlike conventional edge AI, which often assumes moderate hardware capacity and network reliability, Frugal Edge AI explicitly targets low-cost, low-power contexts—those typical of rural, remote, or developing regions. Its ambition is not only technical optimization but also social and environmental equity, aligning with broader goals of responsible AI and the Sustainable Development Goals (SDGs).



Frugal Edge AI in India

Elephant-Train Collision Prevention: Researchers in India developed a smart acoustic and thermal sensor system using TinyML.

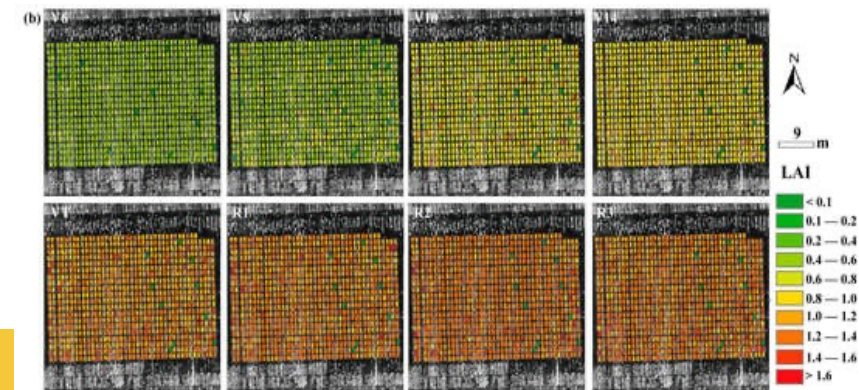
- This is a safety-critical system: incorrect predictions directly affect both wildlife and human lives

Cashew Tree Monitoring: At the Vellore Institute of Technology (VIT), researchers use TinyML-equipped drones to detect fungal diseases in cashew trees with up to 99% accuracy, significantly reducing pesticide use.

- Precision agriculture efficiency vs. risks of inequity, over-automation, and ecological mismanagement

Maize Leaf Analysis: Recent 2025 research utilized a hybrid TinyML platform to identify five types of maize leaf diseases (e.g., Blight, Common Rust) with over 94% accuracy, specifically optimized for low-cost microcontrollers.

- Scaling low-cost AI for food security vs. risks of misclassification, inequity, and over-reliance in vulnerable agricultural systems



Frugal Edge AI in Malawi

Early Disease Detection: Using TinyML sensors to identify plant diseases in the field before they spread, directly supporting the livelihoods of the country's 3.1 million smallholder farmers.

- Scaling AI for inclusive agricultural resilience vs. the risk of amplifying inequality, dependency, and systemic vulnerability

Smart Irrigation: Optimizing water usage through real-time soil and weather data processed on-device.

- Efficiency-driven resource optimization vs. long-term ecological balance and equitable access to water

Environmental & Health Monitoring: Training was provided on using microcontrollers for wildlife conservation and healthcare monitoring.

- Democratizing AI tools through TinyML vs. the risks of misuse, weak oversight, and sensitive data exposure



Continuous Compliance with Legislations for Privacy, IRP & Data Collection

AI Ethics & Principles by Design Framework

Reinforced Benchmarking & Feedback-based Progress Monitoring

Acceptance of AI use in life and job/industry		
20	I am interested in exploring new technological developments for my field of work/in my daily life.	<ul style="list-style-type: none"> Strongly Disagree Disagree Neutral/Neither Agree nor Disagree Agree Strongly Agree
21	I could imagine including AI in my current work or in my daily life.	<ul style="list-style-type: none"> Strongly Disagree Disagree Neutral/Neither Agree nor Disagree Agree Strongly Agree
22	I see the benefit of using AI tools in my current work or in my daily life.	<ul style="list-style-type: none"> Strongly Disagree Disagree Neutral/Neither Agree nor Disagree Agree Strongly Agree
23	Polymakers strongly support AI.	<ul style="list-style-type: none"> Strongly Disagree Disagree Neutral/Neither Agree nor Disagree Agree Strongly Agree
24	(For respondents in employment) The use of AI in my field aligns with what society considers appropriate for the industry.	<ul style="list-style-type: none"> Strongly Disagree Disagree Neutral/Neither Agree nor Disagree Agree Strongly Agree
25	(For respondents in employment) I am the person who decides on the use of AI at my job. (For people in employment)	<ul style="list-style-type: none"> Strongly Disagree Disagree Neutral/Neither Agree nor Disagree Agree Strongly Agree
26	(For respondents in employment) I feel that my organisation would support me in the adoption of AI. (New question for people in employment).	<ul style="list-style-type: none"> Strongly Disagree Disagree Neutral/Neither Agree nor Disagree Agree

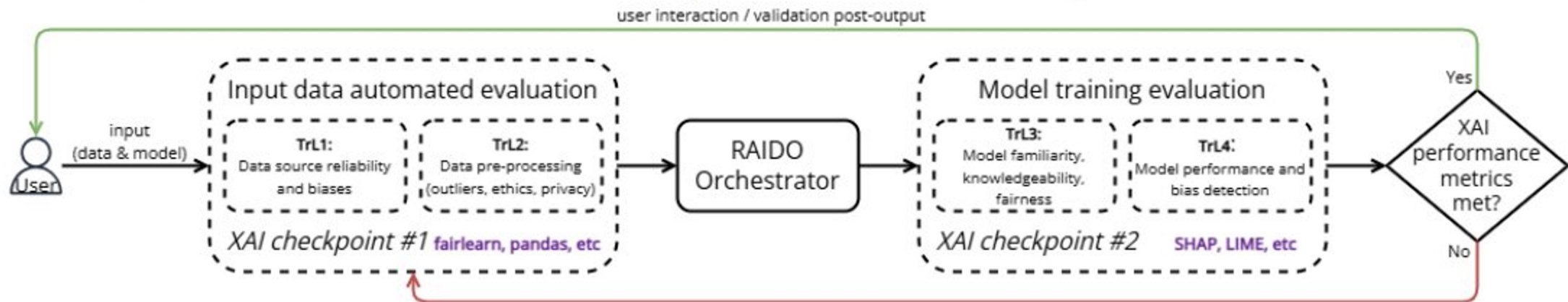


Trinity College Dublin
Coláiste na Tríonóide, Baile Átha Cliath
The University of Dublin

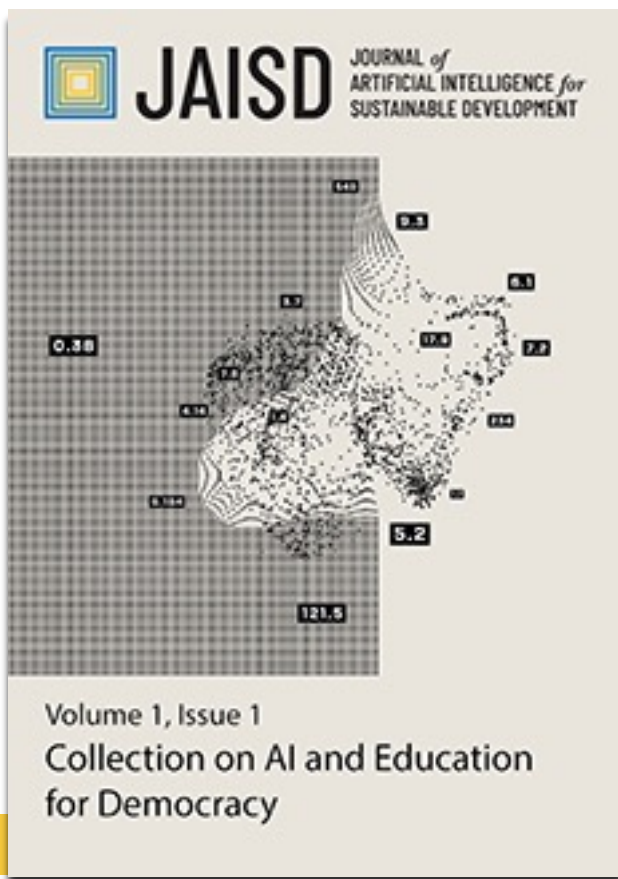


VANESSA NUROCK

Professor of Philosophy at the Université de Côte d'Azur (France) and UNESCO EVA Chair (Ethique du Vivant et de l'Artificiel / Ethics of the Living and the Artificial)



Framework for AI Explainability, Transparency & Trustworthiness



Informed Consent: ensure participants know why their data is being collected, how it will be used, and any associated risks.

Privacy: Protect the identities of participants by anonymizing or de-identifying data.

Transparency: clear purpose of the data collection, the methods used, and potential benefits and risks.

Data Sharing: participants should be aware and have given consent.

Vulnerable Populations: extra precautions when collecting data from children, the elderly, and other vulnerable groups.

Potential Harm: Assess and minimize potential risks to participants. This includes emotional distress, financial harm, or other adverse effects.

Purpose Change: seek fresh consent from participants.

Limitation: avoid over-collection.

Accuracy: data is accurate and represents the truth.

Beneficence: data collection should be for good.

Models vs. Data: storing models, forgetting the data

Access: who has access to the data.

Long-term Storage: ensure secure storage methods.

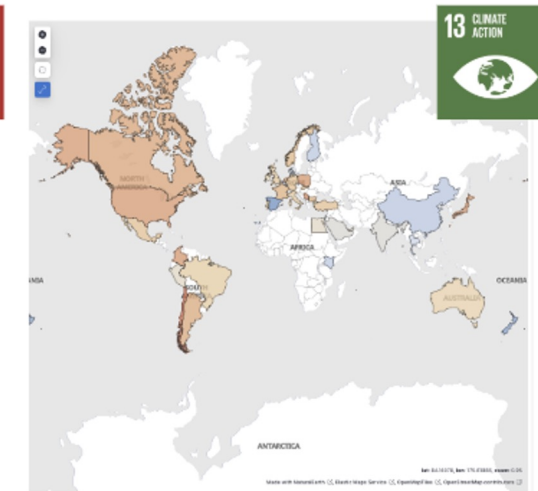
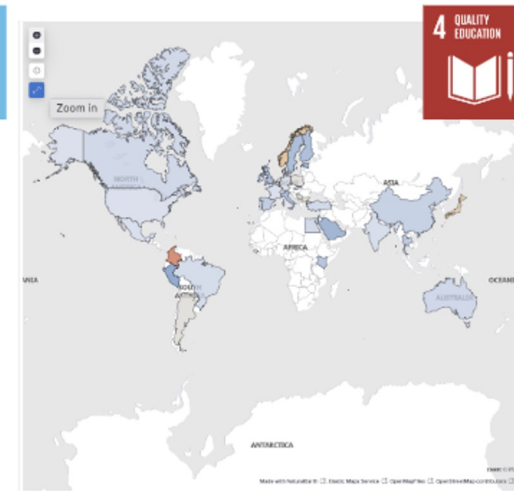
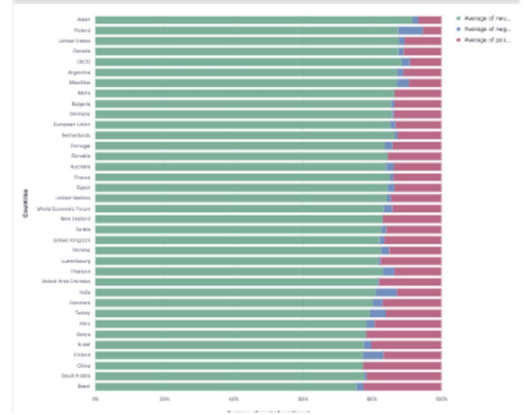
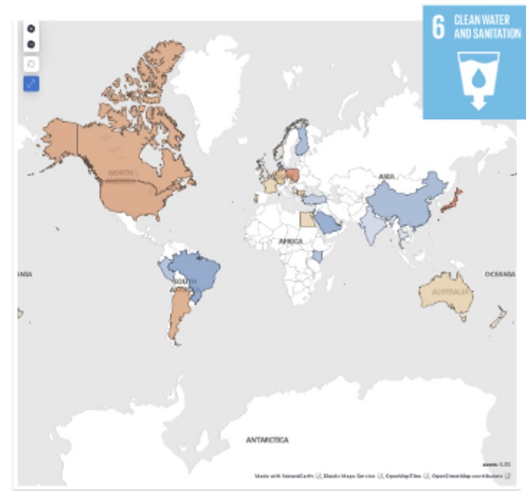
Feedback: offer participants feedback or results from the study if they express interest.

Regulation and Legislation: adhere to local, national, and international data protection laws and regulations.

Cultural Sensitivity: understand and respect cultural norms and traditions when collecting data

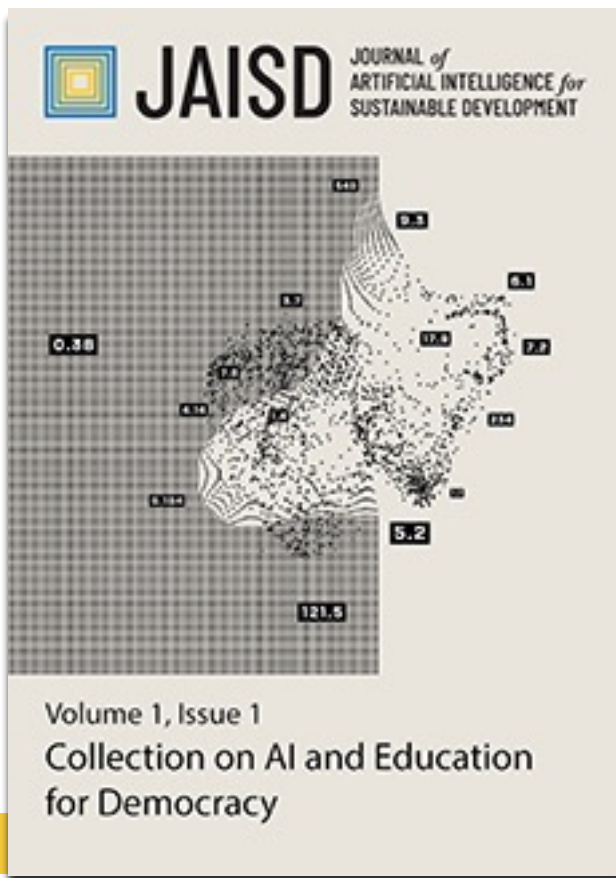
- Compute sentiment analysis (using VADER) on title + text of OECD AI policies translated
- Compare geographically the neutral sentiment on the AI policies to identify tendencies
- Differentiate between SDGs to explore the variability across the 17 targets and their topics

Sentiment Bias Aware.



ai4gov-project.eu  101094905





Transparency: AI algorithms should be transparent in terms of how they work and how decisions are made – XAI.

Bias and Fairness: It's crucial to identify, reduce, and disclose biases to ensure fairness in decision-making.

Accountability: determine who is responsible for AI decisions.

Privacy: protect the privacy of individuals when processing their data.

Data Security: safeguard this data against breaches and unauthorized access.

Autonomy: People should always have a choice, especially concerning decisions that significantly affect their lives.

Informed Consent: Users should be informed when their data is being processed by AI and have a clear understanding of how the AI system uses their data.

Explainability: AI decisions should be interpretable and explainable.

Generalizability and Robustness: AI models are not overfitted to their training data and can generalize well to real-world situations.

Economic and Social Impacts: Consider the broader societal and economic effects of AI for good

Long-term Considerations: longer-term implications of AI, including the potential for systems to evolve or be used in ways not originally intended.

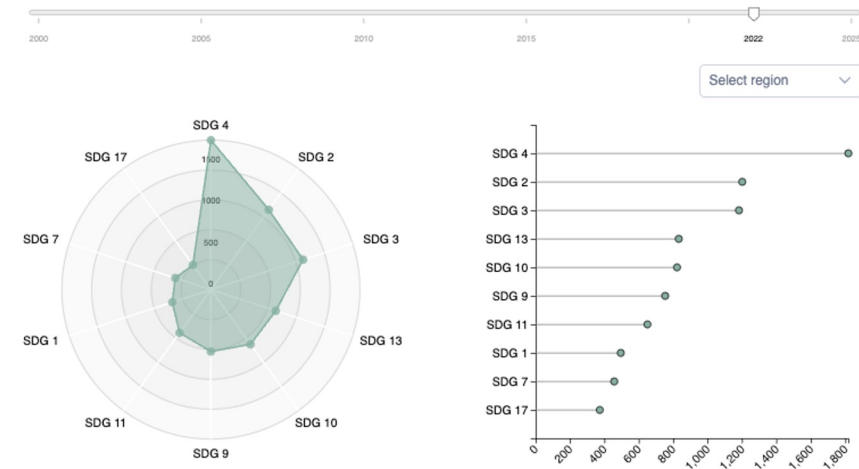
Environmental Impact: consider the environmental footprint and strive for sustainable AI research.

Continual Monitoring: AI systems, especially those deployed in dynamic environments, should be continuously monitored to ensure they are behaving as expected.

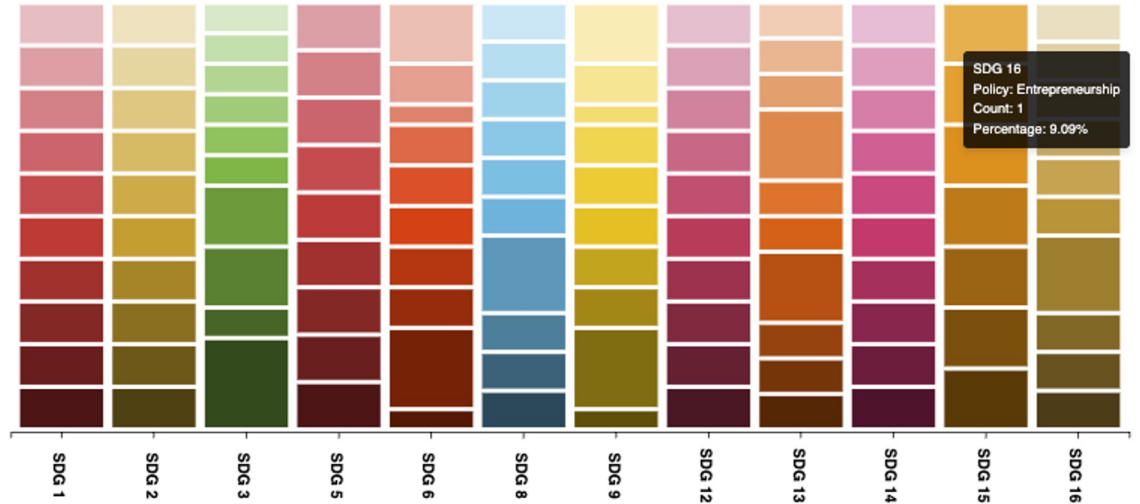
Stakeholder Participation: Involve relevant stakeholders, including those affected by AI systems, in the design, development, and deployment processes.

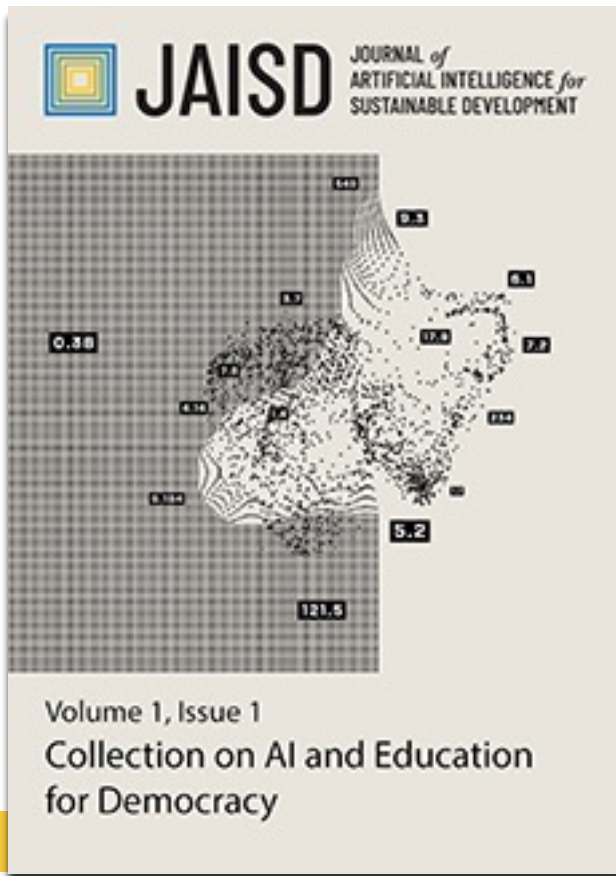
Regulation and Standards: Align AI practices with existing regulations and contribute to the development of ethical standards for AI.

- Evaluate the amount of SDG-classified topics across time
- Compare by geographic world regions to explore prioritisation allowing for comparison
- Encode the SDG topics based on wikidata concepts identified in the textual documents independently of their language



Coverage Bias Aware.





- Avoiding Bias:** confirmation bias (favoring information that aligns with one's existing beliefs) or availability bias (relying on immediate examples).
- Transparency:** clearly communicate the methods and tools used in the analysis so that others can understand and potentially reproduce the results.
- Overreach:** Do not make claims or conclusions that go beyond what the data actually supports.
- Accuracy:** Ensure that interpretations are based on accurate and robust findings. Avoid cherry-picking data or results to support a particular narrative.
- Full Disclosure:** Present any limitations, uncertainties, or assumptions associated with the analysis. This allows for a more nuanced understanding of the results.
- Conflict of Interest:** Be transparent about any potential conflicts of interest that might influence the interpretation or presentation of the results.
- Sensitivity:** Be aware of the broader social and cultural context when interpreting data.
- Feedback Loop:** Consider the potential feedback loop effects where the interpretation of data analysis can influence future data collection and results.
- Stakeholder Consideration:** Think about who is affected by the interpretation of the data and ensure that their interests and perspectives are considered.
- Cultural Context:** Especially in global or multicultural studies, understand the cultural nuances and be wary of interpreting data through only one cultural lens.
- Ethical Implications:** Consider the broader ethical implications of any conclusions drawn, especially if they may lead to actions or policies that impact people's lives.
- Peer Review:** Encourage peer review of findings and interpretations to ensure validity and mitigate potential biases.
- Translating to Policy:** If data interpretation is used to inform policy or business decisions, ensure that the recommendations are ethically sound, justifiable, and in the best interest of those affected.
- Honesty:** Always approach data interpretation with honesty, and avoid the temptation to manipulate or selectively present results for personal or organizational gain.
- Continual Learning:** Recognize that interpretations might change as more data becomes available or as methods evolve. Be open to updating or revising interpretations in the light of new evidence.

- Integration of cognitive science with computational social science.
- Empirical framework for bias detection in AI discourse.
- Use of semantic linking to align media content with AI taxonomy.
- Identification of cognitive mechanisms shaping AI adoption narratives.
- First large-scale framework connecting cognitive biases to AI innovation adoption.

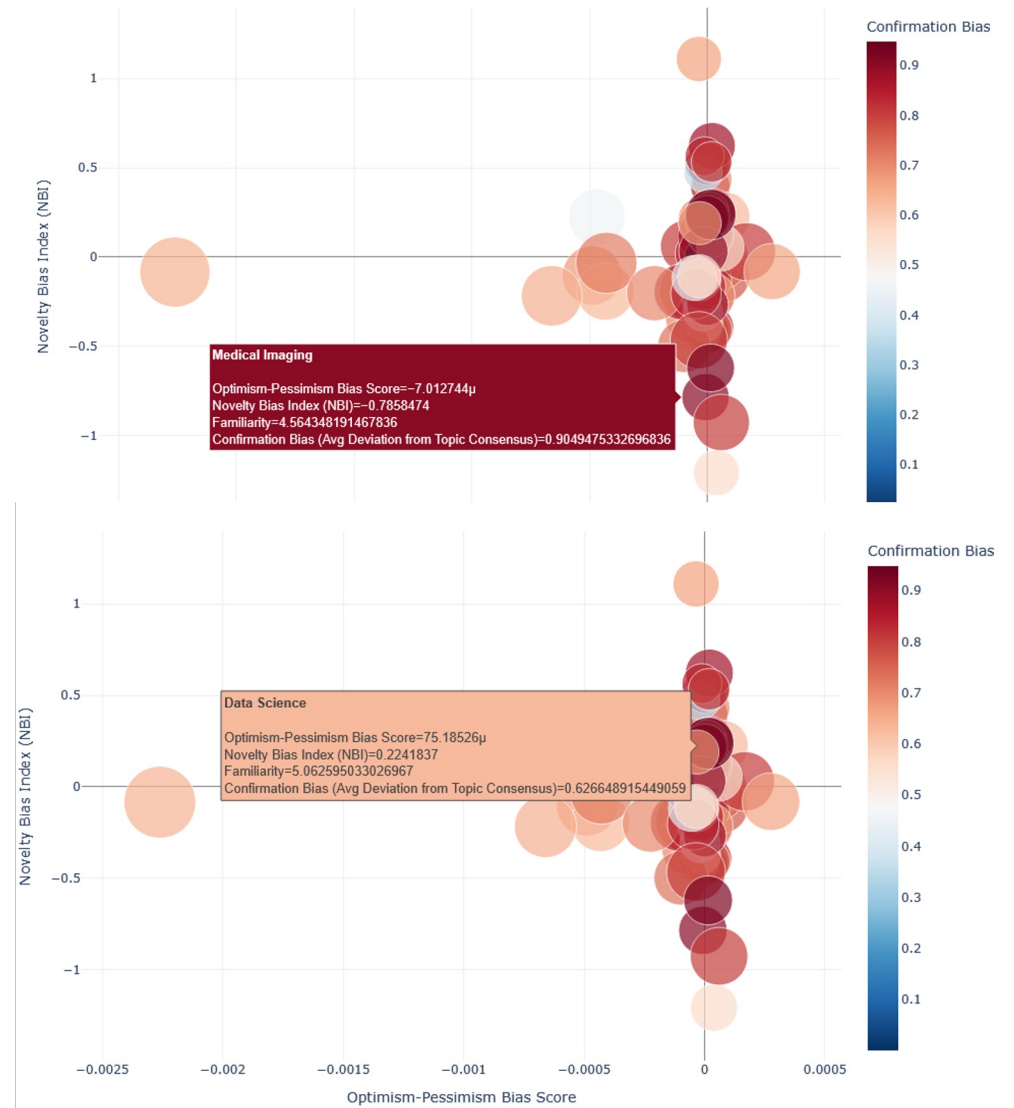
Cognitive Bias Aware.



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List of tools (921)

[Eticas Bias](#)

Technical United States Uploaded on Mar 24, 2025

An open-source Python library designed for developers to calculate fairness metrics and assess bias in machine learning models. This library provides a comprehensive set of tools to ensure transparency, accountability, and ethical AI development.

Objectives: Fairness Robustness

Related lifecycle stage(s): Operate & monitor, Build & interpret model, Collect & process data

[Behavior Elicitation Tool](#)

Technical, Procedural France, European Union Uploaded on Mar 24, 2025

Behavior Elicitation Tool (BET) is a complex-AI system that systematically probes and elicits specific behaviors from cutting-edge LLMs. Whether for red-teaming or targeted behavioral analysis, this automated solution is Dynamic Optimized and Adversarial (DAO) and can be configured to test the robustness precisely and help to have a better control of the AI system.

Objectives: Robustness Safety

Related lifecycle stage(s): Deploy, Verify & validate, Build & interpret model

[AIRO \(AI Risk Ontology\)](#)

Educational Ireland Uploaded on Jan 29, 2025

The AI Risk Ontology (AIRO) is an open-source formal ontology that provides a minimal set of concepts and relations for modelling AI use cases and their associated risks. AIRO has been developed according to the requirements of the EU AI Act and international standards, including ISO/IEC 23894 on AI risk management and ISO 31000 family of standards.

Objectives: Transparency

Related lifecycle stage(s): Operate & monitor, Verify & validate

[COMPL-AI](#)

Technical Switzerland, European Union Uploaded on Jan 24, 2025

COMPL-AI is an open-source compliance-centered evaluation framework for Generative AI models

Objectives: Related lifecycle stage(s)

Overview Tools Metrics About the catalogue [Contribute to the catalogue](#)

CarefulAI: Prompt-LLM Improvement Method (PLIM)

Website

Educational United Kingdom Uploaded on Dec 9, 2024

When working with large language models (LLMs), accuracy is important. However, there is a lack of understanding of the co-dependency between LLM outputs and prompts. Existing LLM benchmarks do not specify this; they allude to historical accuracy scores on LLM benchmarks that may not be relevant to the end user. In addition, LLMs are usually dynamic in practice. Their behaviour is not static, but changes over time, and often cannot be explained by LLM providers. Users, therefore, can only partially depend upon LLM benchmarks. In practice, to make LLMs fit for purpose and safe, users are required to constantly test Prompt-LLM outputs for specific cases. This can be time-consuming.

CarefulAI's approach to this is based on the discovery that by serving a model with a standard set of end-user-specific examples of questions and answers—validated by the end-user community (with each prompt validated by a minimum of 3 subject matter experts/end users), the time taken to get acceptable answers is significantly reduced (tenfold). In addition to getting Prompt-LLM combinations that are deemed safe, the approach enables sector/subject matter prompt benchmarking against multiple models.

PLIM is designed to make benchmarking and continuous monitoring of LLMs safer and more fit for purpose.

Website GitHub Hugging Face

About the tool

You can click on the links to see the associated tools

Developing organisation(s): CarefulAI

Objective(s): Performance

Impacted stakeholder(s): Consumers Regulators

Country of origin: United Kingdom

Type of approach: Educational

Maturity: Implemented in multiple projects

Usage rights: Fee-based

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SCOPE

RISK MANAGEMENT STAGES

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Assess

Assess risks & impacts

Define

Govern

Treat

Treat: Cease risks & impacts

PURPOSE(S)

Filter by...

SUBMIT A METRIC

If you have a tool that you think should be featured in the Catalogue of AI Tools & Metrics, we would love to hear from you!

SUBMIT

List of technical metrics (130)

This page includes technical metrics and methodologies for measuring and evaluating AI trustworthiness and AI risks. These metrics are often represented through mathematical formulas that assess the technical requirements for achieving trustworthy AI in a particular context. They can help to ensure that a system is fair, accurate, explainable, transparent, robust, safe, or secure.

[Accuracy](#) 168 related use cases

Accuracy is the proportion of correct predictions among the total number of cases processed. It can be computed with:

Accuracy = (TP + TN) / (TP + TN + FP + FN), where:

TP: True positive

TN: True negative

FP: False positive

FN...

Objectives: Performance Robustness

[Mean Intersection over Union \(IoU\)](#) 35 related use cases

Mean Intersection over Union (IoU) is the area of overlap between the predicted segmentation and the ground truth divided by the area of union between the predicted segmentation and the ground truth.

For binary (two classes) or multi-class segmentation...

Objectives: Performance Robustness

[Anonymity Set Size](#) 32 related use cases

Website GitHub Hugging Face

Apache 2.0

Data scientist

Developer

Other

Academia

Business

Government

Always up to date

International

ai responsible performance benchmarking ilm



<https://oecd.ai/en/catalogue/tools>

Bias Detector Catalogue

The Bias Detector Catalogue stands as a pioneering tool, met expansive repository represents a concerted effort by innovat tailored to diverse stages of the training process. From data c Catalogue is a testament to the collective determination to m



Bias in Automated Speaker Recognition Accuracy: MODERATE Cost: MODERATE

AIF360: AI Fairness 360 toolkit	Accuracy: HIGH	Cost: LOW
FairMLHealth	Accuracy: UNKNOWN	Cost: LOW
<p>Source: https://github.com/KenSciResearch/fairMLHealth Type: MITIGATION Programming Language: PYTHON</p> <p>Description: FairMLHealth is a healthcare-specific tool for bias analysis. It provides machine-learning fairness, healthcare applications, and variation analysis.</p> <p>Applicability: HEALTHCARE</p> <p>Limitations: The 'fair' range to be used for these metrics requires judgement on the part of the analyst.</p> <p>References: Ahmad et al., (2020). Fairness in Machine Learning for Healthcare. Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining. https://doi.org/10.1145/3394486.3406461.</p>		
Mitigating Unwanted Biases with Adversarial Learning	Accuracy: HIGH	Cost: LOW
Themis-ml: A Fairness-Aware Machine Learning Interface for End-To-End Discrimination Discovery and Mitigation	Accuracy: UNKNOWN	Cost: UNKNOWN
Bias in Automated Speaker Recognition	Accuracy: MODERATE	Cost: MODERATE
Bias Assessment Metrics and Measures	Accuracy: UNKNOWN	Cost: UNKNOWN
Biaslyze	Accuracy: UNKNOWN	Cost: LOW



<https://cluster-ai4gov.euprojects.net/>



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