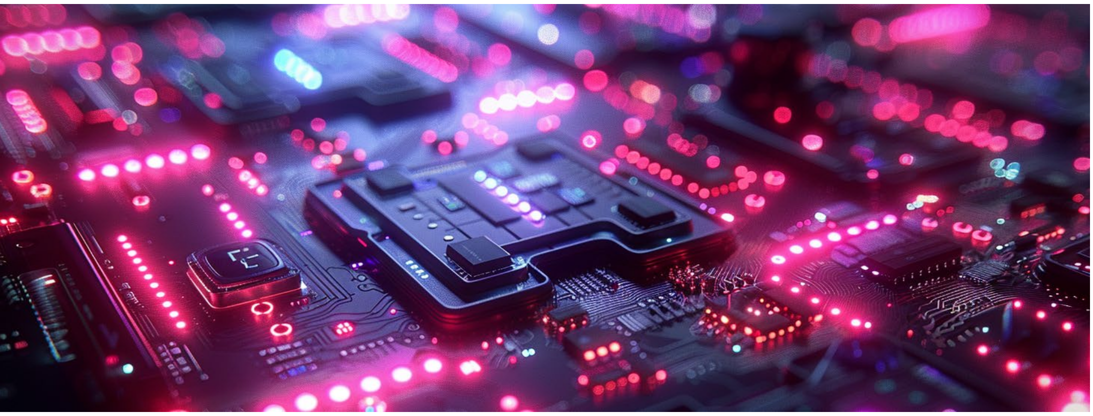
January 2026

Newsletter #4

In AI-DAPT we are building an end-to-end approach to data–AI pipelines that are reliable in real operational settings: they are observable, adaptable over time, and engineered with trustworthiness in mind. During the first half of the project, the consortium consolidated the baseline services that underpin this vision—services that translate the project's methodological foundations into reusable building blocks that can be deployed across domains. Together, these foundations enable AI-DAPT to move beyond "one-off models" and instead support repeatable, auditable, and evolvable AI pipelines.



AI-DAPT Baseline Services

AI-DAPT is developing an end-to-end approach for data and AI pipelines that can operate reliably in real-world settings. These pipelines are designed to be observable, adaptable over time, and built with trustworthiness as a core principle. During the first half of the project, the consortium focused on the baseline services that underpin this vision, translating the project's methodological foundations into reusable platform capabilities that can be applied across domains. Baseline services refer to the core platform functions that make AI development and operation repeatable, trustworthy, and scalable. Rather than treating each use case as a one-off pipeline, these services capture the essential capabilities that consistently determine whether AI can move from experimentation to deployment.

In practical terms, these baseline services target the recurring bottlenecks that typically slow down or undermine industrial AI—fragmented data assets, inconsistent quality, limited traceability across pipeline steps, and insufficient monitoring and control after deployment. By addressing these challenges as common platform services (rather than ad-hoc per project / pilot), AI-DAPT establishes a more systematic pathway from data foundations to deployable and maintainable AI, while reinforcing trustworthiness-by-design through transparency and human oversight.

Data Foundations that Scale

Reliable AI starts with reliable data. One of the key outcomes of the first phase of AI-DAPT has been the consolidation of strong data foundations that can support AI systems beyond experimentation and into real operational settings. Our Deliverable D2.1 captures this work by defining a structured, data-centric approach to preparing data for AI in a way that is repeatable, transparent, and fit for long-term use.

AI-DAPT addresses common challenges such as fragmented data assets, limited documentation, hidden bias, and unclear provenance by treating data design (Fig. 1) as a first-class activity.

Instead of assuming data readiness, we introduce systematic processes for identifying data that are fit for a given AI purpose, harvesting them in a controlled manner, and making their characteristics explicit through documentation and metadata.

This includes clear descriptions of datasets, their origin, intended use, and the assumptions under which they were collected (Fig. 2). A central contribution of this work is the emphasis on data quality and valuation.

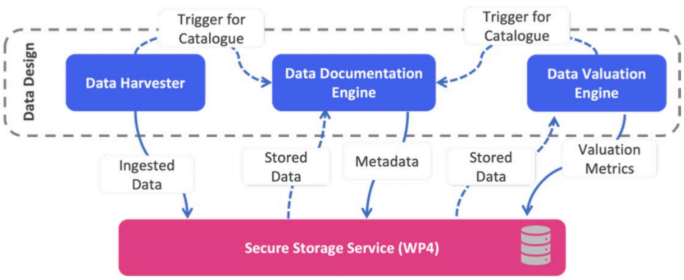


Fig.1 Data Design Services

AI-DAPT goes beyond basic checks by promoting methods to assess data fitness for purpose, surface potential bias, and understand how different data elements influence model behaviour. This allows data scientists and domain experts to make informed decisions early in the pipeline, reducing downstream risks and costly rework.

Traceability is another core aspect of the data foundations. By systematically capturing data lineage and provenance, AI-DAPT enables teams to track how data evolve across pipeline steps, supporting auditability, reproducibility, and regulatory compliance. This is particularly relevant in high-impact domains where transparency and accountability are essential. Together, these foundations form the backbone upon which more advanced data preparation, model design, and lifecycle management services can be built.

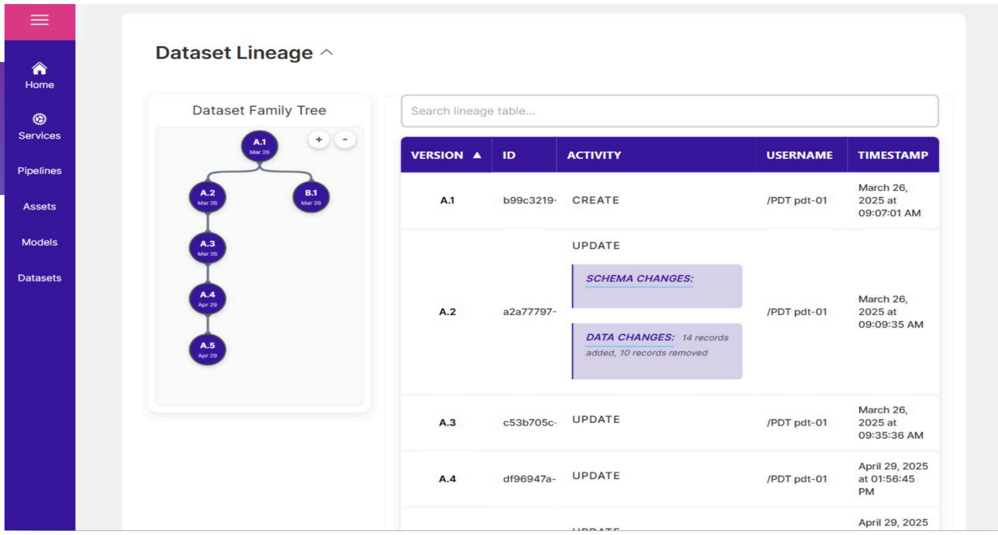


Fig.2 Data Documentation Engine

Hybrid Science–AI Models as a Foundation for Trust

One of AI-DAPT's distinguishing contributions lies in its systematic support for hybrid Science–AI models, which combine domain knowledge and physics with data-driven learning. As outlined in our Deliverable D3.1, the project moves beyond purely black-box machine learning by integrating first-principles models, physical laws, and expert knowledge directly into AI pipelines. This approach is particularly relevant in industrial, energy, and health contexts, where data may be incomplete or noisy, regulatory constraints are strict, and well-established scientific and engineering knowledge can be systematically exploited to guide and constrain AI behaviour.

AI-DAPT demonstrates how science-guided components can be coupled with machine learning models at different levels of integration, ranging from loosely coupled correction models to tightly integrated architectures that embed domain constraints into the learning process. This coupling improves robustness, reduces data requirements, and supports more stable behaviour under changing operational conditions. Importantly, it also enhances interpretability, as model behaviour can be partially explained through known physical or causal relationships rather than inferred correlations alone.

Domain knowledge can be incorporated into the AI pipeline at different stages to complement data-driven modeling. Depending on the use case, this knowledge may take the form of science-based simulators, reduced-order models, or domain-informed feature engineering processes. When simulators are available, they can be integrated as explicit pipeline components to support hybrid learning strategies such as residual learning, where machine learning models refine simulator outputs, or parameter estimation, where simulator parameters are learned directly from data. All such configurations are defined and orchestrated at the pipeline level, enabling flexible design and evaluation of domain-aware AI workflows.

AI-DAPT further supports uncertainty-aware training, evaluation, and explainability, allowing domain experts to inspect model behaviour, assess robustness, and determine when adaptation or retraining is required. As a result, hybrid Science–AI models become governable, monitorable, and evolvable assets rather than static, one-off artefacts.

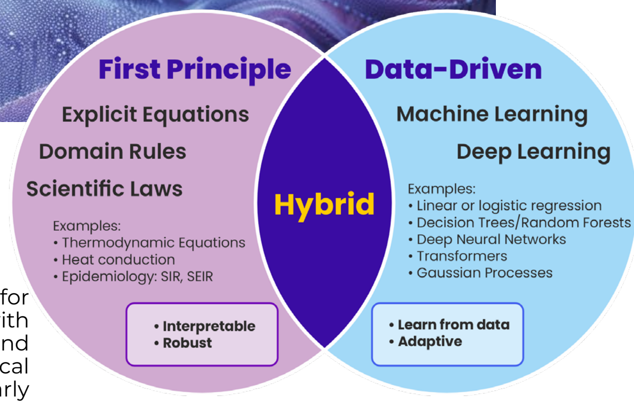


Fig.3 The spectrum between first-principle models and data-driven approaches

Collaboration Highlights

HELEN

AI-DAPT has strengthened its collaboration across the European AI ecosystem through continuous engagement with partners, sister projects as well as actively participating in thematic networks such as HELEN.

Key moments included active participation in ADRF 2025 last September, with discussions on trustworthy and efficient AI adoption, the project's plenary meeting in Caparica in October (photo bellow), and continued momentum at EBDVF 2025 in November, reinforcing sustained collaboration and knowledge exchange across the community.

https://www.ai-dapt.eu/

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The project has received funding from the European Union's Horizon 2023 research and innovation program under the Grant Agreement No. 101135826

Submit to our ICE 2026 Special Session

ICE 32nd Edition
International Conference on Engineering, Technology and Innovation

Join us in shaping the future of trustworthy AI by submitting your research and innovation to the special session we are organizing at the ICE IEEE/ITMC 2026 Conference (Porto, Portugal).

Advancing Adaptive and Trustworthy AI Pipelines: From Data Foundations to Lifecycle Orchestration and Analytics. We welcome papers on topics such as:

- Data-centric AI practices
- AI pipeline orchestration and automation (e.g. MLOps)
- Hybrid modeling and Explainable AI
- Lifecycle management and monitoring of AI systems
- Trust, safety, ethics, and regulatory alignment in AI solutions
- Applications demonstrating impactful AI across sectors through robust pipelines

Important dates:

- Full paper submission: 27th March
- Notification of acceptance: 8^{th} May
- Conference: 22^{nd} – 24^{th} June 2026

See more at: **ice-conference.org**