MatCHMaker
Materials Characterisation & Modelling

MatCHMaker Results & Industrial Exploitation

This project has received funding from the European Union's Horizon Europe research and innovation programme under grant agreement Nº 101091687.

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What We Will Cover Today

- Industrial use cases & adoption
  Speakers: Alexandre Ouzia, Patrice Tochon, Maxime Hubert
  Examples from HeidelbergMaterials and Genvia showing how MatCHMaker tools were applied in real industrial settings
- The MatCHMaker Open Repository
  Speakers: Iacob Crucianu, Otilia Bularca, Jesper Friis
  Presentation of the repository concept, semantic framework, interoperability approach and live demo
- Tools, validation & exploitation outlook
  Speakers: Geoffrey Daniel, Giuseppe Minafra
  Overview of microscopic analysis tools, lessons learned, post-project roadmap and exploitation perspectives

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Industrial uses and adoption

MatCHMaker Results & Industrial Exploitation

Alexandre Ouzia (HeidelbergMaterials)
Patrice Tochon (Genvia) & Maxime Hubert (CEA)

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HeidelbergMaterials Use Case

Rising EU ETS pressure on cement

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Carbon permits now exceed the cost of clinker production in most regions

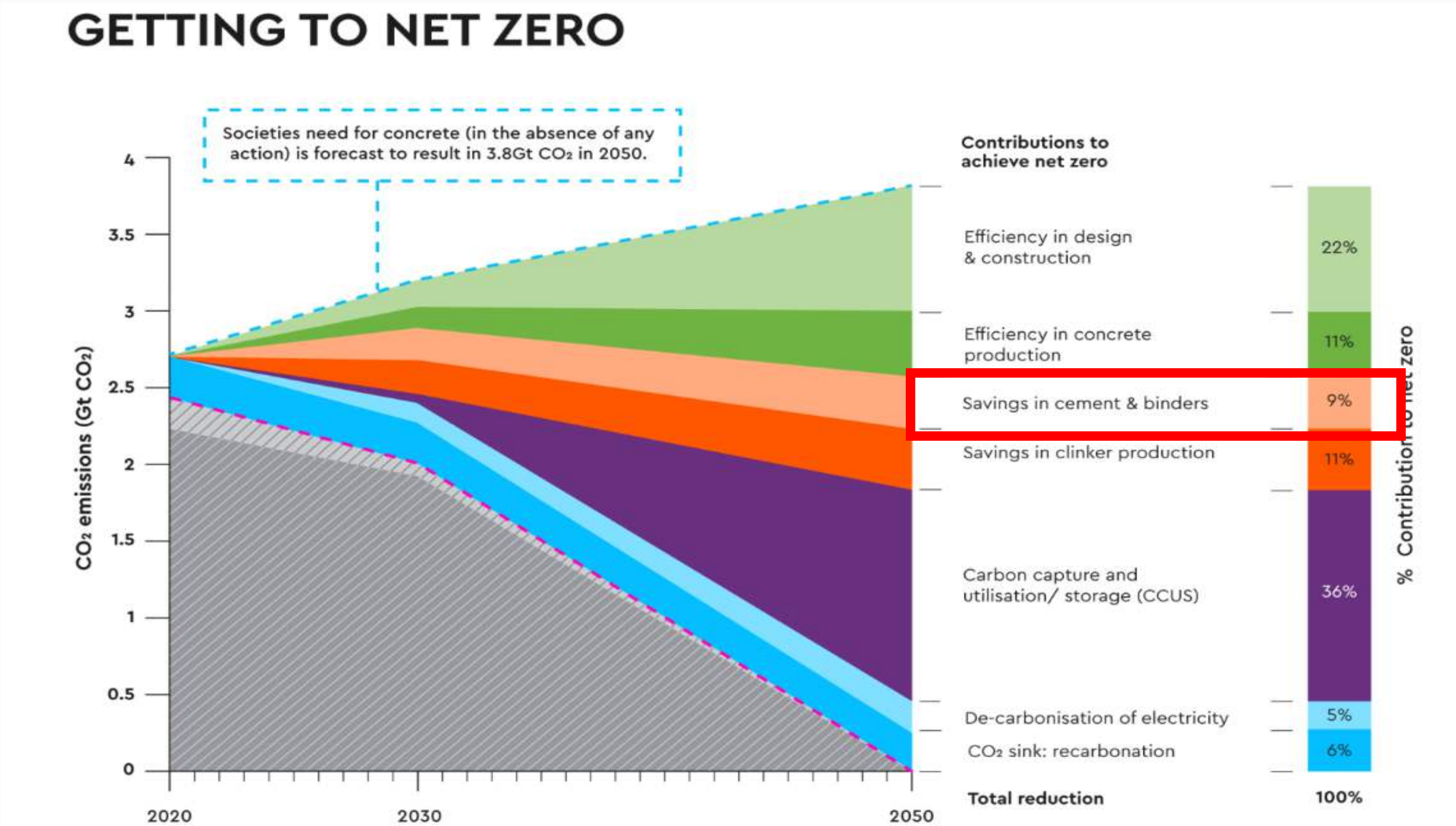
74 €
per tonne of CO_2
the price today (Q2 2026)

100+ €
peak in 2023
structurally above 60 € since 2021

× 7
in less than 10 years
from ≈ 10 € (2017) to 74 € (2026)

The cement industry is one of the first heavy emitter forced to act — and SCMs are the most actionable lever

Net-zero roadmap — the role of SCMs



Reminder — EU carbon price

74 € / t CO_2 · Q2 2026

Savings in cement & binders

9 %

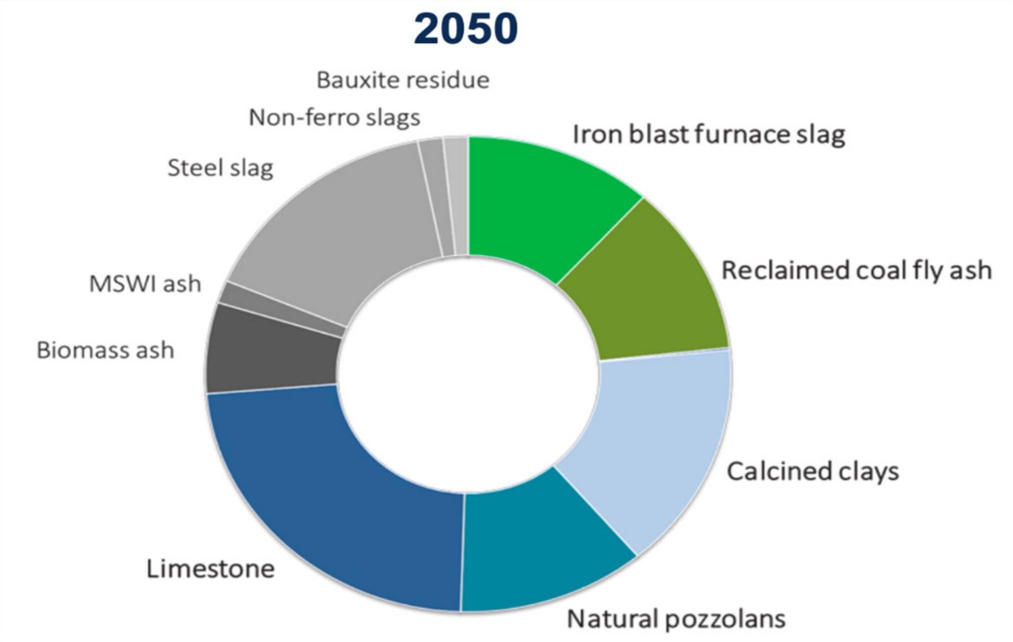
of the 2050 net-zero contribution

Shortest deployment timeline of all decarbonisation levers.

Lower clinker via SCMs is actionable now — but how low can we safely go?

There is no silver bullet recipe

≥ 10 SCM families expected on the European market by 2050



Source: CEMBUREAU, 2020

After limestone, calcined clays are the most promising

Legacy supply (BFS, fly ash) shrinks as upstream industries decarbonise.

1. Each SCM has its own chemistry, reactivity and microstructural develpment
2. Each blend must be requalified on strength, workability, durability and H&S
3. The industry needs transversal, reproducible workflows

This is where MatCHMaker comes in

Image analysis — one workflow, two outputs

BSE + EDX → cluster-based segmentation → phase fractions + quartz screening

① Phase quantification & SCM reactivity

The challenge

Standard NMR routes for SCM reactivity are unreliable in iron-bearing systems.

The MatCHMaker tool

Semi-automatic clustering on BSE + EDX → phase-resolved volume fractions.

Industrial outcome

→ Feeds the strength model

→ Now in use at HM for new SCMs

② Quartz screening — Health & Safety

The challenge

Residual respirable quartz in calcined clays is a regulated occupational hazard.

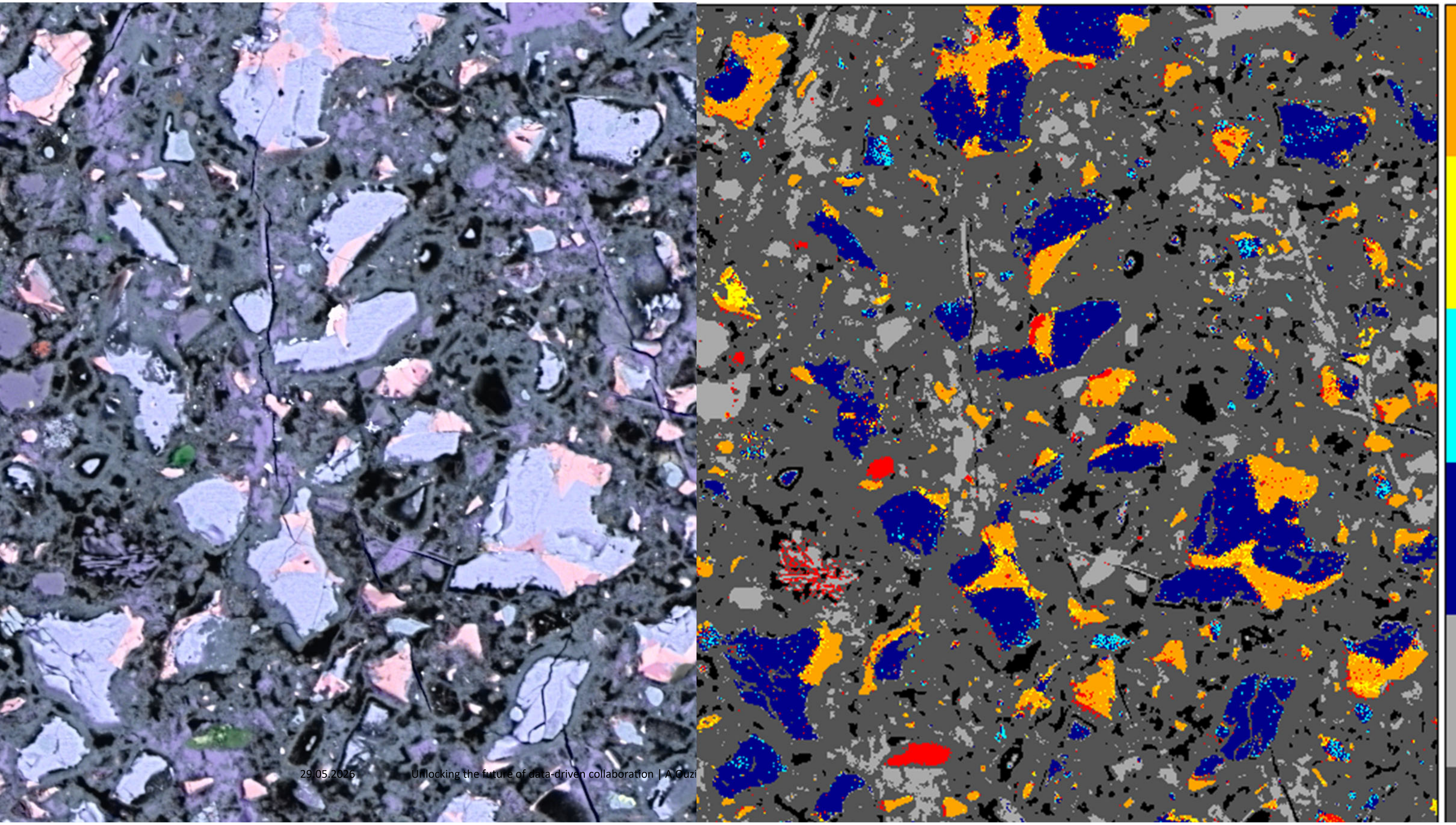
The MatCHMaker tool

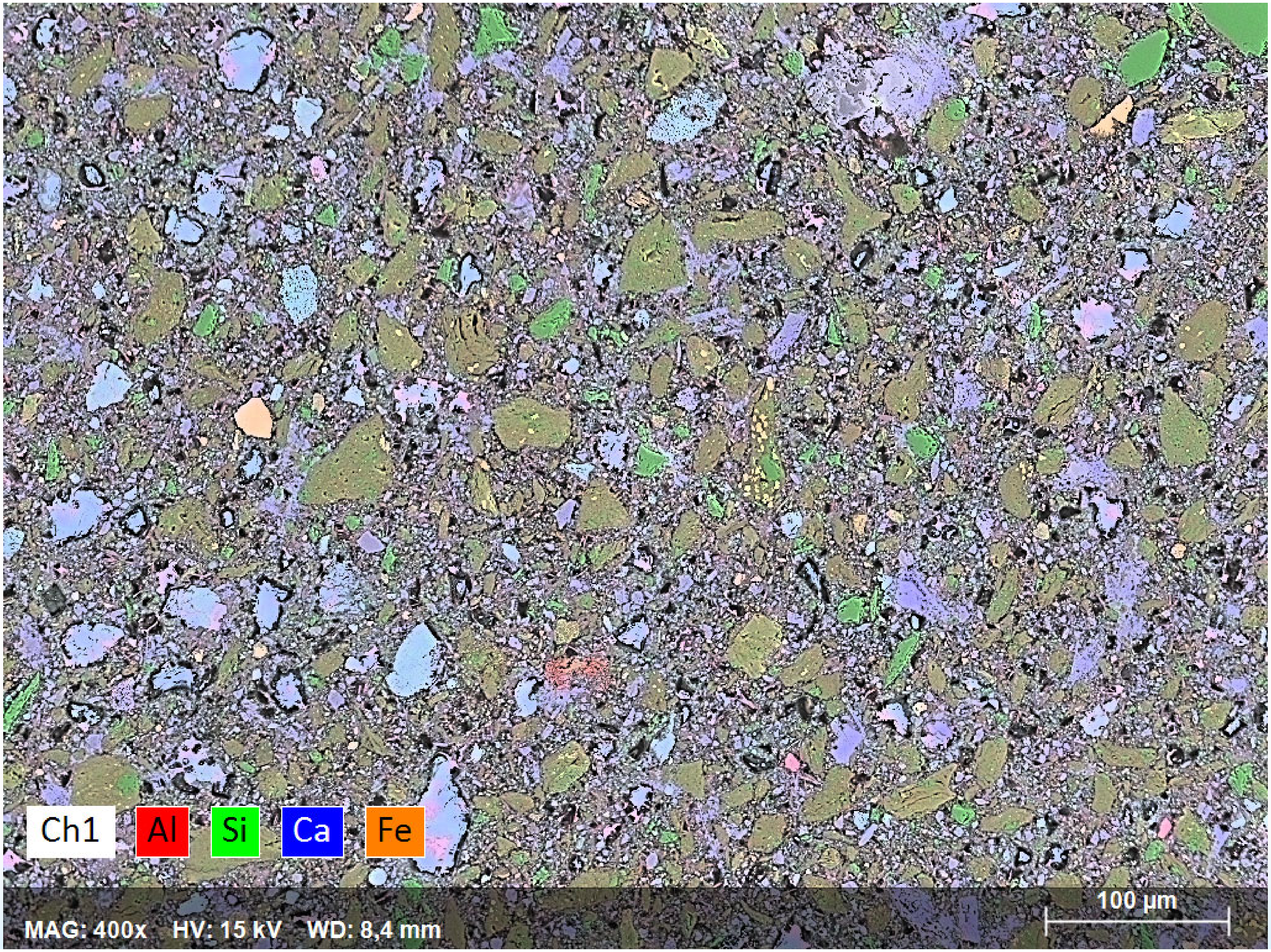
Same clustering workflow isolates fine quartz from the clay matrix — no extra acquisition.

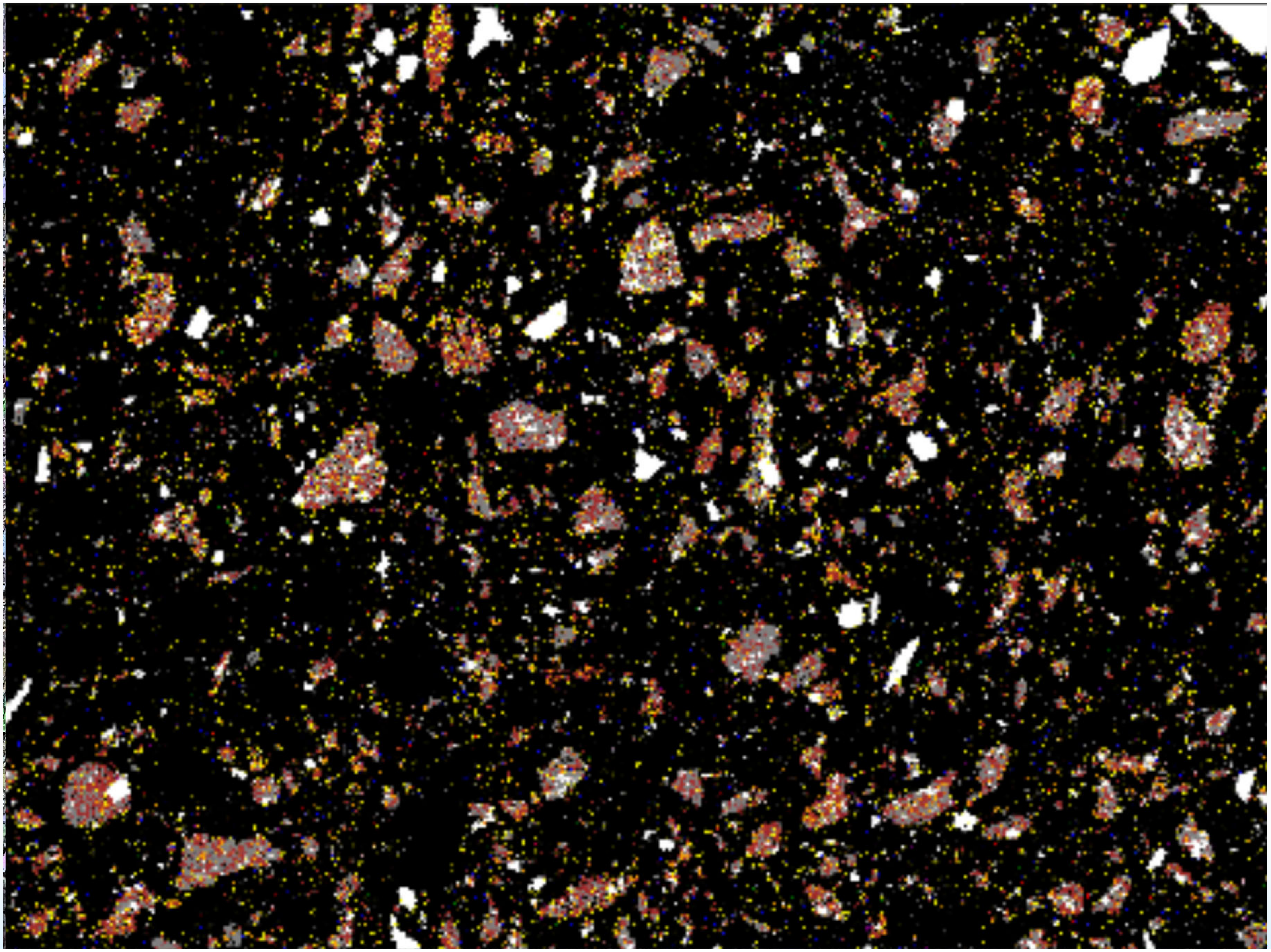
Industrial outcome

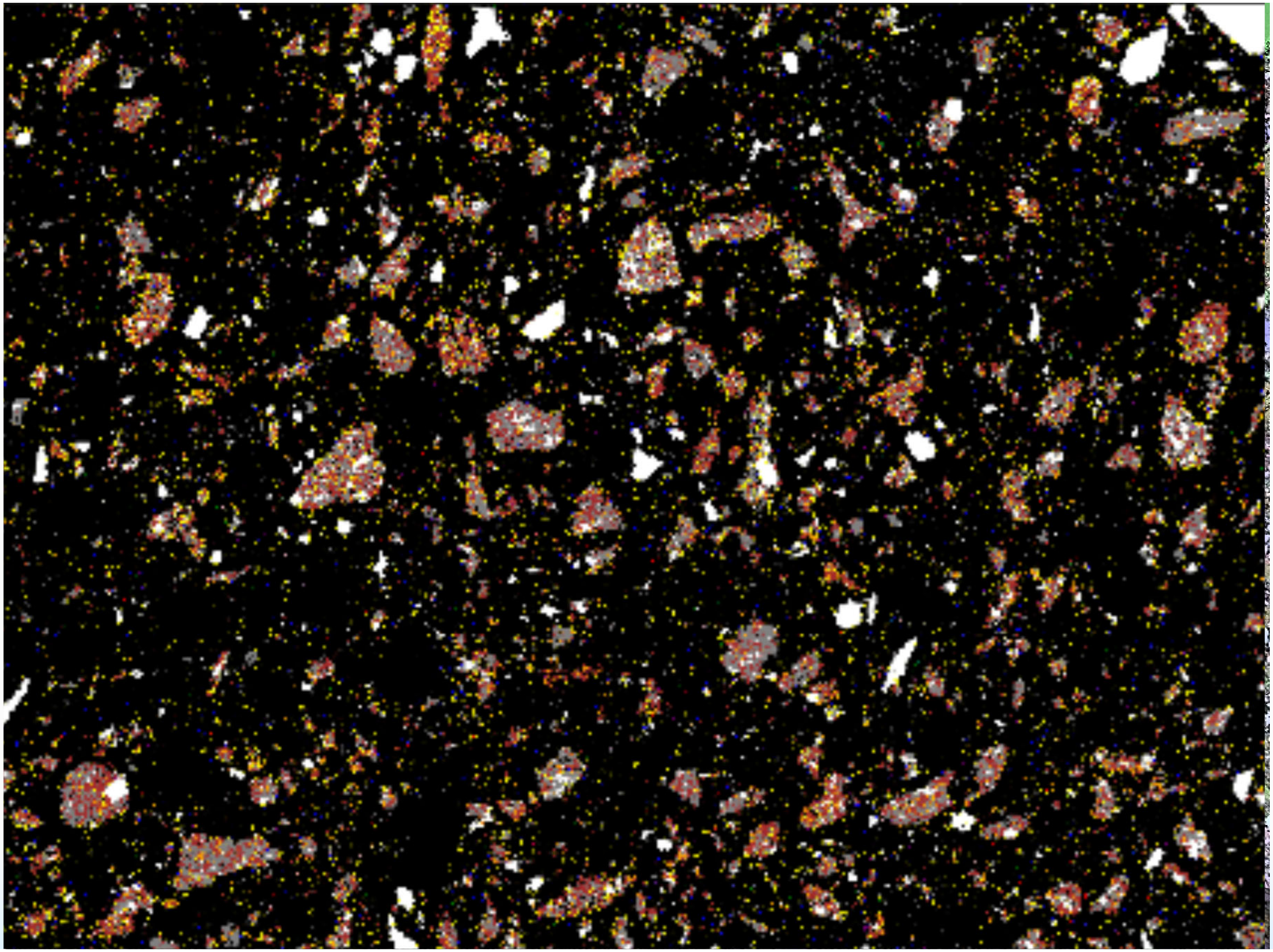
→ Set the max calcined-clay loading in a commercial product

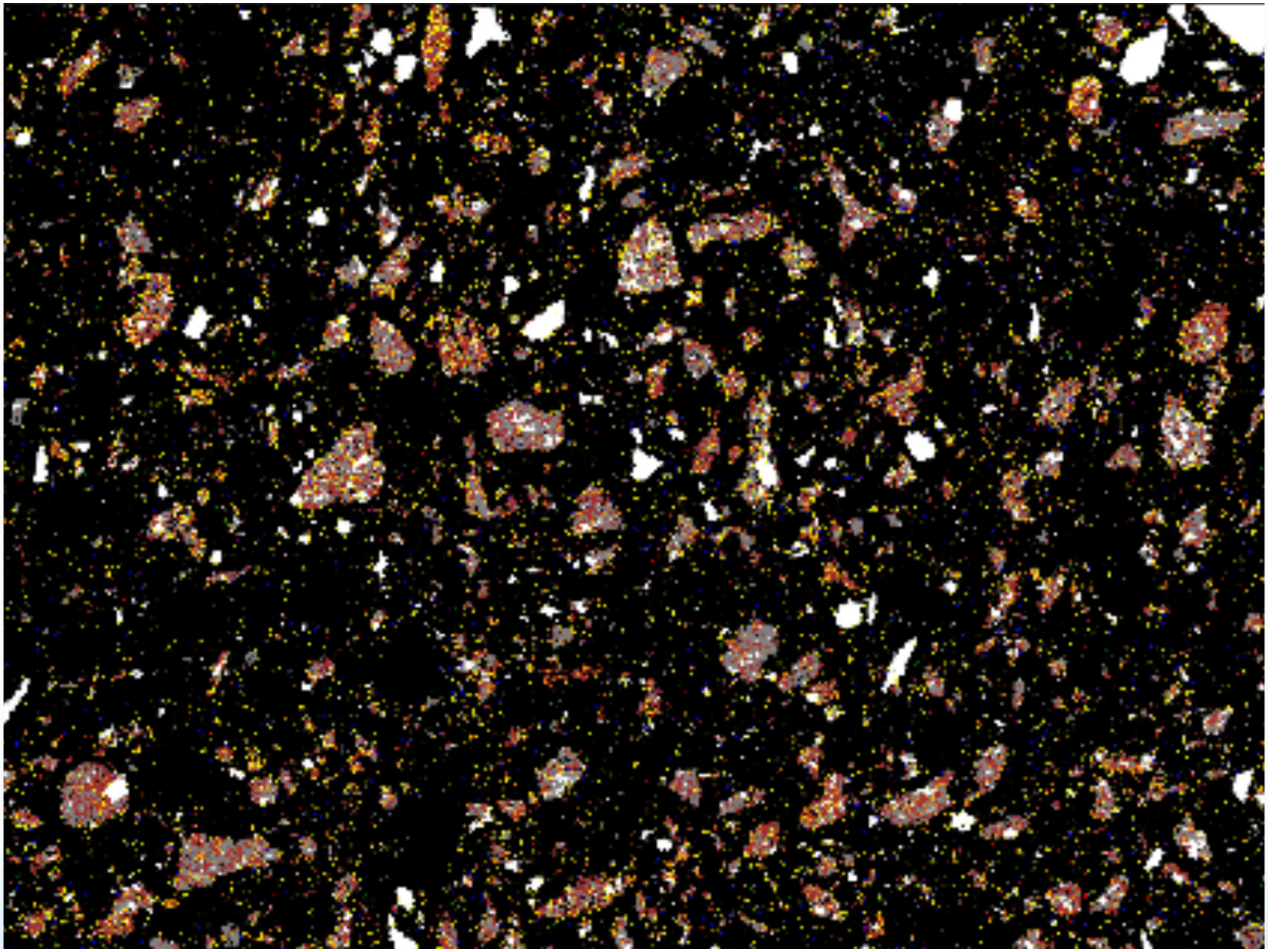
→ Cleared the regulatory gate




Ch1
Al
Si
Ca
Fe
100 µm
MAG: 400x HV: 15 kV WD: 8,4 mm



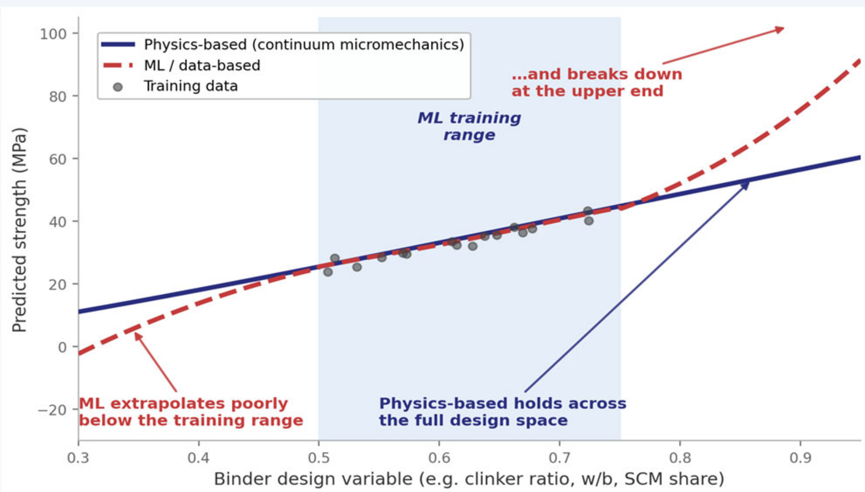




Predicting binder performance — optimum under constraints

Strength is one dimension; durability and microstructure are the others

Strength — ML vs physics-based



Data-based (ML)

Covers many mix variables at once — but fails in extrapolation

Physics-based — robust across the full design space

Durability — how far can we lower the clinker?

MatCHMaker quantifies the clinker-substitution ceiling

≈ 50 % clinker range for LC3 under European mild-exposure

Resistivity-based model

Aligned with the RILEM TC 298-EBD protocol.

Accelerated carbonation (matter for durability) campaign

Pastes + mortars under controlled conditions — gives the carbonation floor on clinker substitution.

Industrial impact for low-carbon cements

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Identified Problem

EU ETS pressure + a 2050 portfolio of ≥ 10 SCMs → industry must lower clinker AND requalify every new SCM on strength, durability and H&S. Bespoke campaigns per binder do not scale.

Proposed Solution — MatCHMaker tools

Image-analysis workflow

Phase quantification + SCM reactivity + quartz screening

Two complementary strength models

Data-based (ML) for broad mix exploration + physics-based for robust extrapolation

Resistivity-based durability indicator

Empirical model aligned with RILEM protocol

Benefits

Minimum clinker, sufficient performance

Lowest clinker (= CO_2) that still matches the performance of current products

Health & safety cleared

Quartz screening unlocked a commercial calcined-clay product

Reusable across SCMs

Same workflow now applied to 5 SCM families beyond LC3

Way Forward

Extend to the 2050 SCM mix

Natural pozzolans, recycled fines, alternative slags

Concrete-scale validation

Cross-check against natural-exposure data

Couple ML × physics

Use physics to regularise ML where data is sparse

Already industrialised

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Calcined-clay cement plants in operation today

Tema plant — Ghana

First calcined-clay cement plant of its scale in operation

5+	SCM families now characterised at HM with the MatCHMaker workflow
CEM II/B-M	Commercial calcined-clay cement — H&S cleared by quartz screening
≈ 50 %	Clinker range for LC3 under mild European exposure

From characterisation tool to commercial cement — MatCHMaker is helping deliver at industrial scale

Genvia Use Case

Genvia — SOEC for sustainable hydrogen

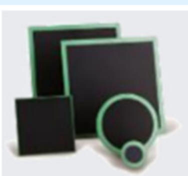
An industrial company scaling Solid Oxide Electrolysis Cells for low-carbon H_2

2021 — Established — built on 15 years of CEA R&D and SLB engineering expertise

150+ — Employees today, across R&D Grenoble, Engineering Clamart, Manufacturing Béziers

40+ — Patents in solid-oxide technologies

Hy2Tech — IPCEI laureate — Wave 1; supported by CEA, SLB, VINCI, VICAT, ARIS



Cell

Stack

Module

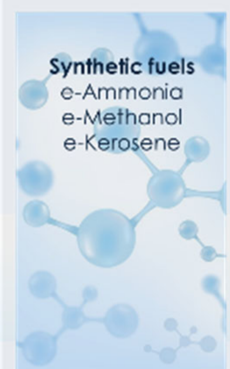
Why SOEC matters

High-temperature electrolysis from water + electricity → low-carbon H_2

Consumes less electricity than alkaline / PEM electrolysers; integrates well where industrial heat is already available.

Hydrogen targets across chemicals, steel, transport and energy demand efficient, durable, competitive production at scale.

Genvia → developing, industrialising and deploying SOEC at industrial scale.



SOEC technology — and the materials challenge

Performance and lifetime depend on how well the Ni-YSZ cermet electrode resists degradation

$ / kg H_2 / hour	kWh / kg H_2	Durability
• Scale up manufacturing • Higher stack power density • Optimise BoP cost	• Optimise reaction conditions • Reduce every joule of loss • Swap electrical for heat	• Zero-defect manufacturing • Reduce cell degradation • Fault-tolerant design

The materials degradation challenge in Ni-YSZ cermet hydrogen electrodes

Degradation mechanisms

- Ni particle agglomeration & migration
- Local depletion of active sites
- Porosity changes · Micro-cracks in the YSZ matrix

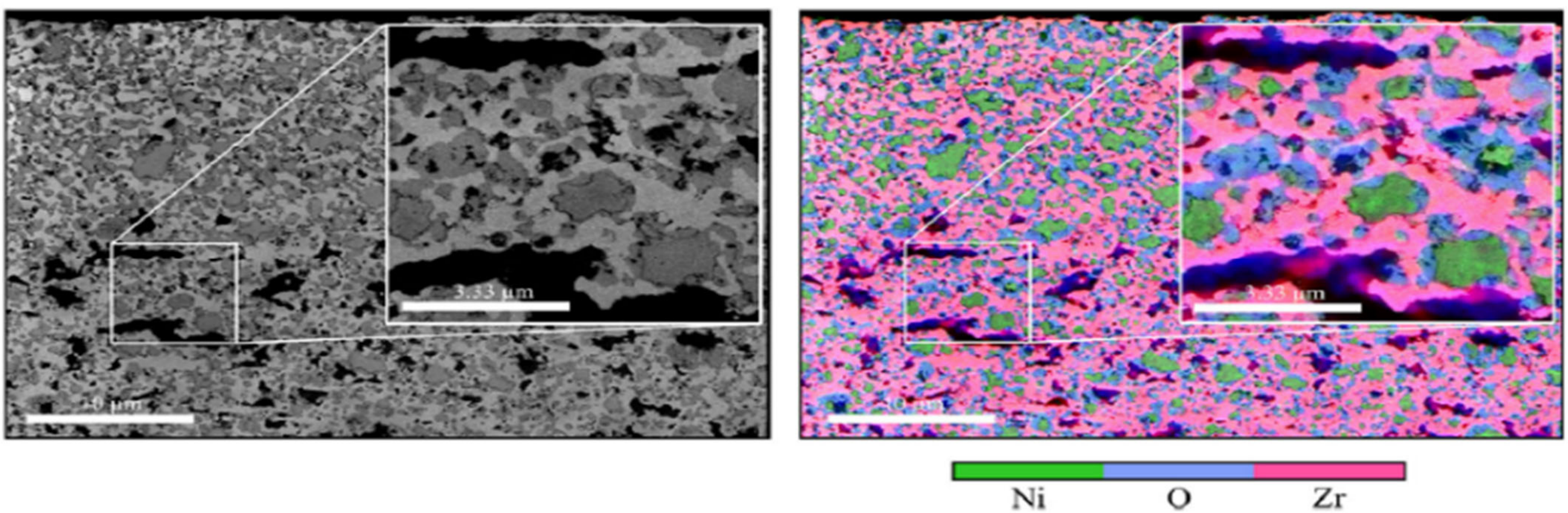
Where MatCHMaker comes in

Two complementary approaches: image analysis of post-mortem microstructures + phase-field modelling of the Ni reoxidation mechanism.

→ Predictive understanding → design guidelines for more robust electrodes.

Image analysis — post-mortem SEM observation

Microstructural examination at different Ni reoxidation times



Left: SEM after 20 min reoxidation

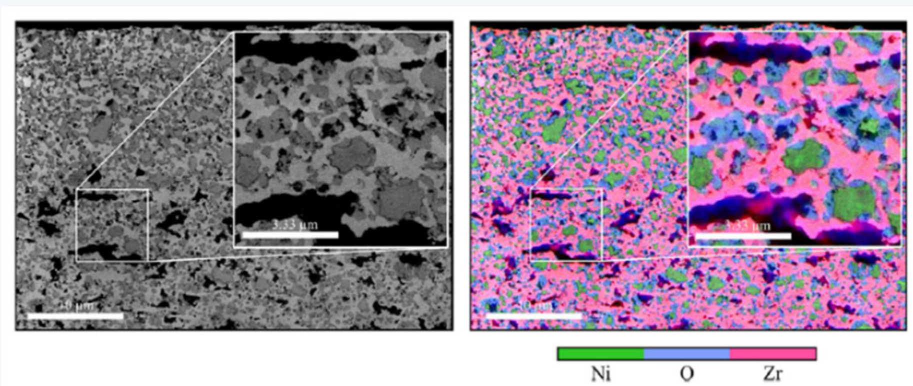
Right: Overlay SEM + EDS · Ni · O · Zr

Post-mortem characterisation is challenging and time-intensive — automation needed

Image-analysis tool — microstructural examination of Ni reoxidation

Post-mortem SEM characterisation is challenging and time-intensive — MatCHMaker delivers a deep-learning segmentation tool that automates phase identification

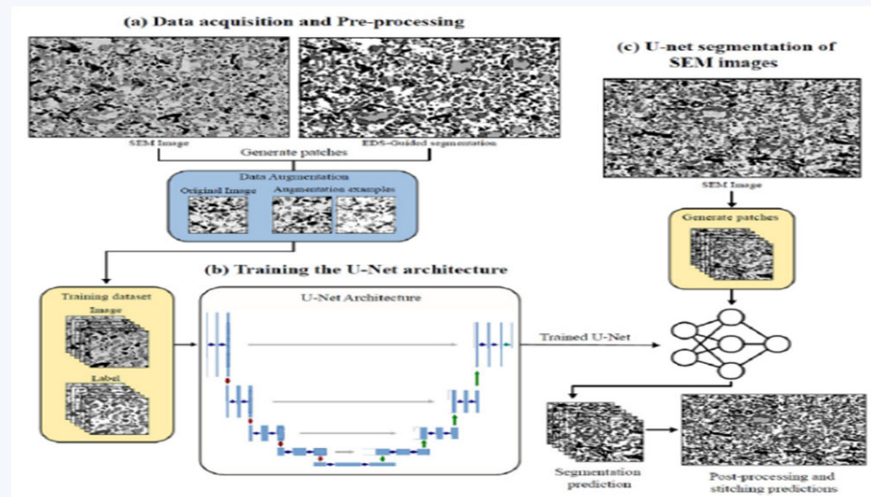
Microstructural examination at different Ni reoxidation times



SEM (left) · Overlay SEM + EDS (right) — Ni · O · Zr

Post-mortem characterisation is challenging and time-intensive — different reoxidation times have been observed for model validation

Deep-learning segmentation — developed during MatCHMaker



- Phase identification (Ni · NiO · YSZ · pores)
- Deep-learning segmentation accelerates analysis

Ref: K. Dia et al., Materials & Design 260 (2025) 115200 — U-Net with EDX-guided labelling

Phase-field model — Ni reoxidation in YSZ

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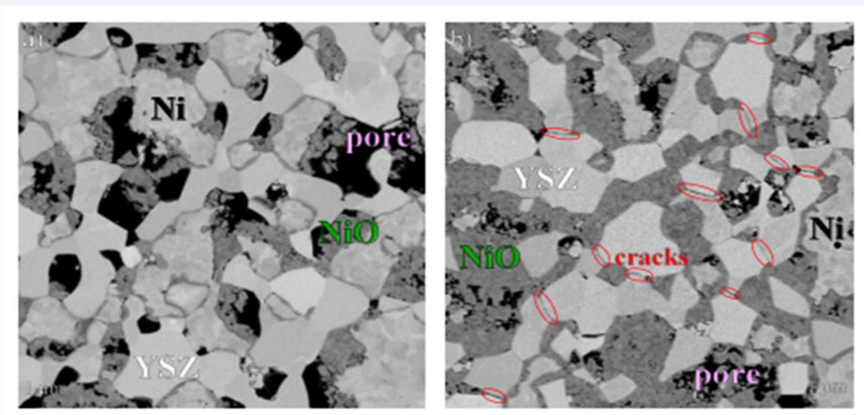
MatCHMaker delivers a validated predictive model of the cracking threshold

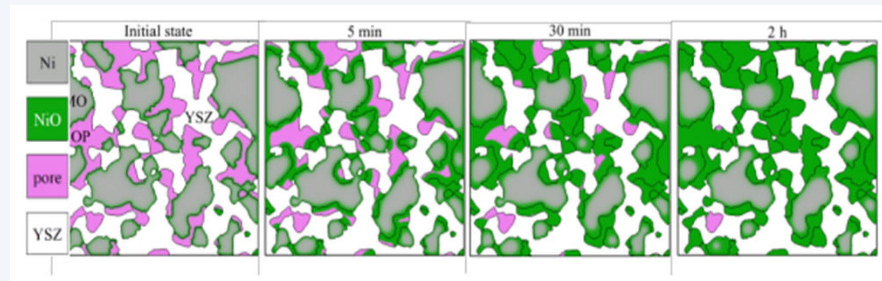
Experimental — SEM at 700 °C



Left: 2 min · Right: 120 min reoxidation

- Reoxidation is complex
- Without a model, the cracking threshold is unknown

Phase-field model — MatCHMaker



Phase distribution: Ni · NiO · pore · YSZ · 10 × 10 μm² functional layer

- Reproduces the Ni reoxidation observed experimentally
- YSZ-backbone stress simulated → crack initiation predicted
- **With the actual microstructure, ≈ 30 min at 700 °C → clear cracks**

S. Fournier et al., Acta Materialia (2026, under review) — PFM of Ni oxidation, oxide growth and mechanical impact

MatCHMaker — industrial impact for SOEC

Identified Problem

Limited performance and lifetime of SOEC technology due to Ni reoxidation → higher cost of hydrogen. Without predictive understanding of the cracking threshold, electrode design is empirical.

Proposed Solution — MatCHMaker tools

Image-analysis tool

Deep-learning segmentation of SEM at different Ni reoxidation times

Phase-field model

Captures oxidation kinetics + stress + porosity closure → predicts cracking

Benefits

Mechanistic understanding

Coupled phenomena (oxide growth + stress + porosity closure) now resolved

Validated predictive model

Cracking now predictable from the actual functional-layer microstructure

Faster post-mortem analysis

Automated U-Net removes the bottleneck

Way Forward

Optimise microstructure

Tune porosity, tortuosity, Ni particle size

Refine operating conditions

Temperature, current density — guided by the model

Manufacturing feedback

Iterate on robust electrode designs at Béziers

Expected — Electrical efficiency 41 → < 39 kWh/kg H_2 · Lifetime 3 → > 5 years

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Open Repository

Presenter(s): Iacob Crucianu, Otilia Bularca (SIMAVI)
Jesper Friis (SINTEF)

The challenge

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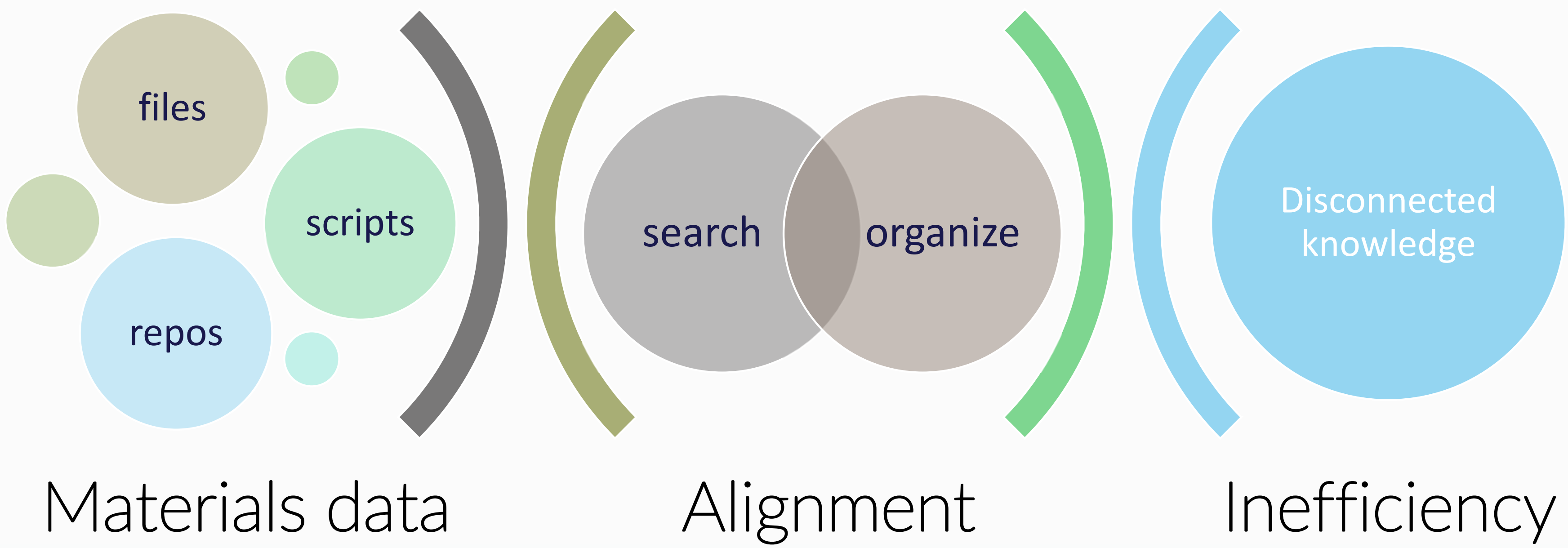
…from data overload to fragmented knowledge



MatCHMaker's approach

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...from storage to connected knowledge

Combines

- Data integration
- Semantic technologies
- AI-driven exploration

Shifts

- From isolated data sets to interoperable workflows
- From manual linking to built-in relationships

MatCHMaker repository

Centralized and collaborative knowledge space

Ontology model & semantic framework

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Ontologies provide a shared language for data

- Define concepts, relationships, and context materials across workflows
- Ensure semantic consistency across characterization & modelling
- Foundation for AI reasoning and advanced analytics

ENABLE:

- Interoperability between systems and domains
- More powerful search and querying
- Machine-readable knowledge structures

Semantic consistency

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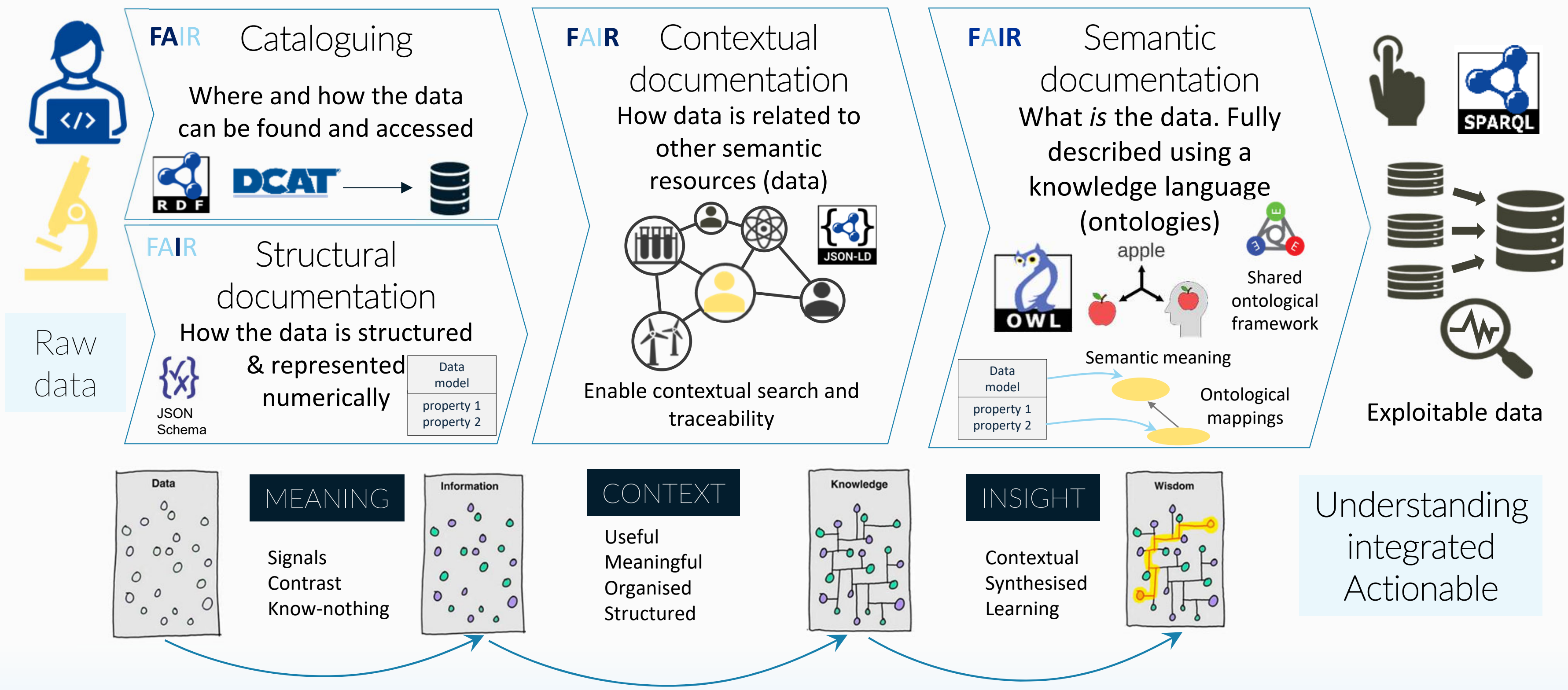

The software used

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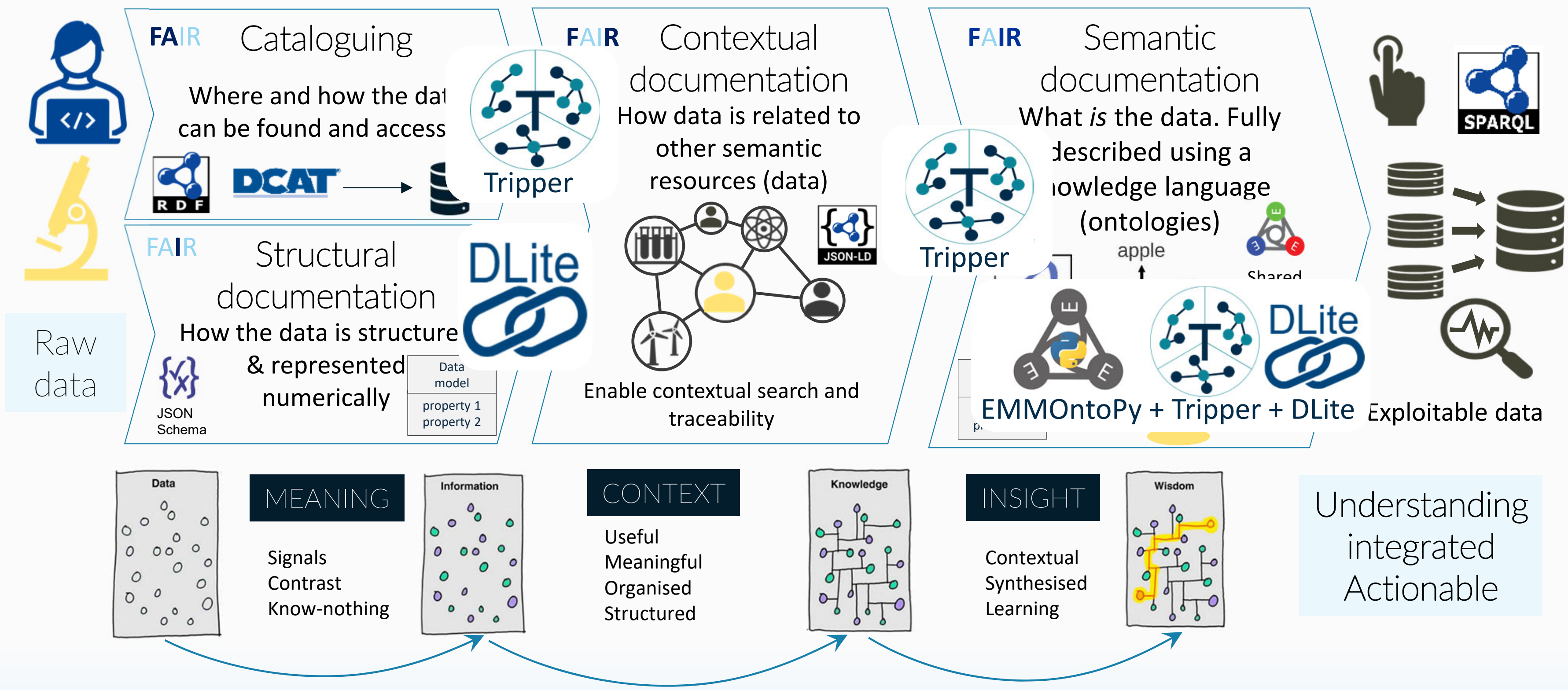

Dedicated domain ontologies to capture use case knowledge

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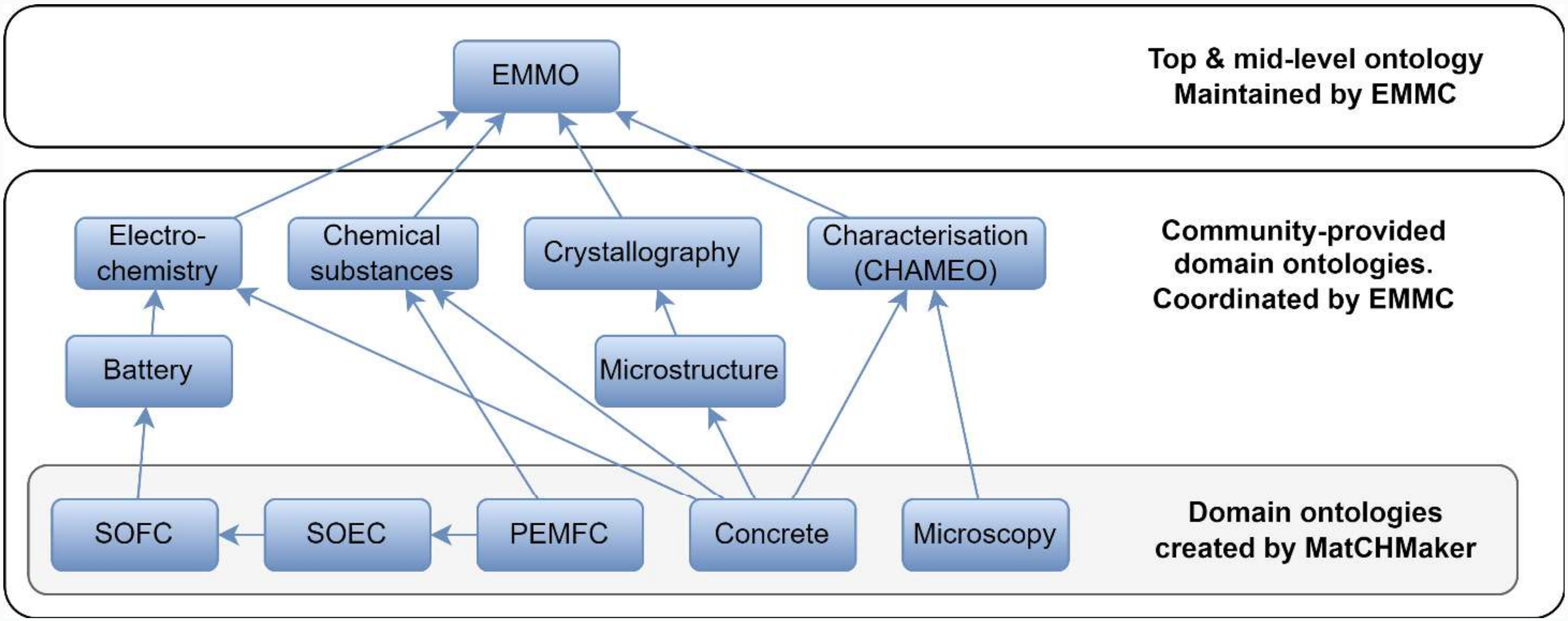

The MatchMaker Open Repository

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Modular, extensible platform

Core capabilities:

- Integration of heterogeneous data sources (streaming, files, repositories)
- Project-based collaborative workspaces
- Annotations linking data with meaning
- Built-in AI tools (LLM + RAG) for insight generation

Designed as a reusable digital asset:

- Adaptable to different domains and use cases
- Supports open and interoperable infrastructures

Industrial Use Cases & Validation

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Applied in real-world industrial and research settings

Demonstrated

- Improved data accessibility and traceability
- Reduced effort in data preparation and alignment
- Enhanced cross-domain collaboration

Lessons learned

- Interoperability requires both technology and common semantics
- User adoption depends on usability and integration
- Value comes from connecting existing workflows, not replacing them

Perspectives

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Adoption & sustainability

Market relevance

- Strong need for data interoperability and AI-ready infrastructures

Integration potential

- Designed to fit into existing industrial & research ecosystems

IP & exploitation

- Flexible models:
- Open components
- Hybrid approaches
- Partner-driven solutions

Focus on value creation rather than one-size-fits-all commercialization

Beyond the project

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Reuse & Ecosystem Embedding

Future focus

Reuse of components and knowledge models
Maintenance through community and partnerships
Integration into broader digital ecosystems

Paths for different stakeholders:

Research infrastructures
Industrial platforms
Open science initiatives

From a single project to a growing, connected ecosystem

From concept to practice

Live demo of the MatchMaker Open Repository

Tools for Microscopic Analysis

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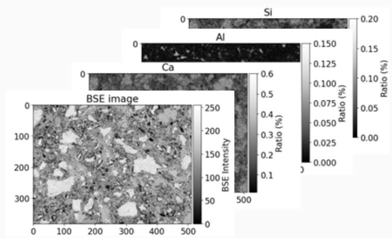
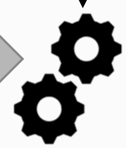
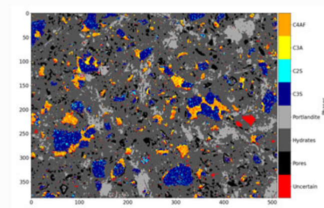
Cement Paste	Input	Process	Output	Benefits and limitations
Semi-automatic workflow for segmentation and phase assemblage	BSE + EDX measurements	Expert knowledge → Semi-automatic process	Segmented image Phase assemblage Uncertainties	👍 Expert's knowledge: less sensitive to acquisition conditions and each step explainable Hydrates unmixing Provides uncertainty ⚠ Expert's knowledge: more time consuming, subjectivity of the user Some phases hard to identify (calcite)
Deep learning model for main phase segmentation	BSE image only	Deep Learning process	Segmented image	👍 Deep learning only: fully automatic Necessitates only BSE ⚠ Limited to the main phases Sensitive to acquisition conditions



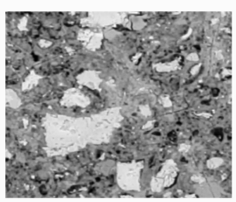
BSE + EDX measurements



Semi-automatic process

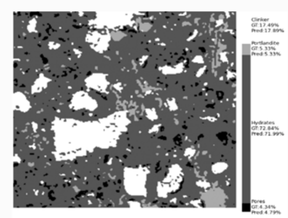


Segmented image
Phase assemblage
Uncertainties



BSE image only

Deep Learning process



Segmented image

Tools for Microscopic Analysis

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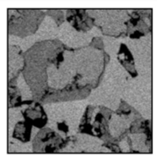
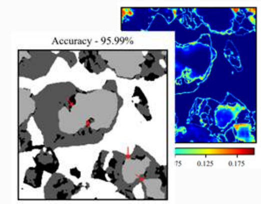
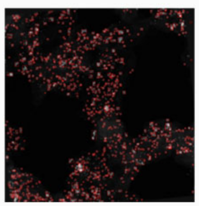
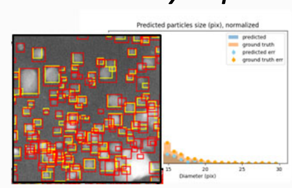
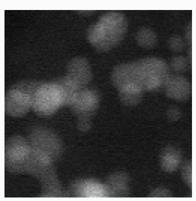
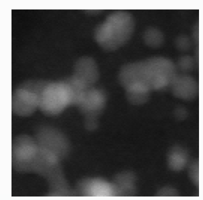
	Input	Process	Output	Benefits and limitations
SOFC				
Deep Learning segmentation	 *BSE measurement*	*Deep Learning process*	 *Phase segmentation* *Uncertainty map*	Fully automatic + Requires BSE only → x100 speed-up vs current method Provides uncertainty Sensitive to acquisition conditions
PEMFC				
Nanoparticle identification and size distribution	 *TEM image*	*Deep Learning process*	 *Identification box of particles* *Distribution of sizes*	Deep learning only: fully automatic Uses single TEM image Small nanoparticles hard to detect Some complex overlaps
TEM image denoising	 *TEM image short-time acquisition*	*Deep Learning process*	 *Denoised image*	Deep learning only: fully automatic Requires only short-time acquisitions → x4 to 10 speed-up Possible loss of contrast

Roadmap after project-end

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Evolve the MatCHMaker **Open Repository** *from a project output into a sustainable, scalable research infrastructure*.

Phase 1 – Consolidation
Months 0-12 post-project

✓ Core Service Stabilization
Focus on the industrial-grade stabilization of core services

✓ Governance Formalization
Execution of formal joint-ownership and governance agreements among the consortium

✓ Open Science Excellence
Achieving full operational alignment with FAIR principles

Phase 2 – Extension & Integration
Months 12–24 post-project

✓ Domain Expansion
Extending the platform's capabilities to additional high-growth materials domains

✓ Federated Ecosystem Integration
Implementing progressive integration into European data spaces and marketplaces to maximize cross-domain interoperability

✓ Community Onboarding
Scaling the user base by onboarding external researchers

Phase 3 – Sustainability & Scale-up
24+ months post-project

✓ Value-Added Service Launch
Deploying premium services, including secure private data spaces for industry, advanced AI analytics, and customized plugin development.

✓ Hybrid Financial Model
Transitioning to a sustainable business model

✓ Ecosystem Pillar Positioning
Solidifying MatCHMaker as a stable, indispensable building block within the European materials data ecosystem

Market Placement Strategy

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The **MatCHMaker Open Repository** is positioned as a first-of-its-kind "Distributed Data and Knowledge Mesh".

It acts as a sophisticated **digital bridge between academic research and industrial application**.

The platform supports sustainable innovation with an objective in reduction in material design costs and improvement in development time through the integration of data, physics-based models, and AI-driven approaches.

Primary Market B2B Industrial

Focused on materials data management within the **Construction**, **Energy**, and **Mobility** sectors. These industries represent a combined market opportunity driven by the need for rapid material upscaling to meet decarbonization targets.

Secondary Market Scientific & Tech

Includes **R&D departments**, **academia**, and **ICT/AI developers** seeking curated, high-quality datasets for machine learning training, as well as **Standardization Bodies**.

Application Domains & Expansion

Core Domains: Validated through three critical low-carbon use cases: Low-carbon Cement, Solid Oxide Fuel/Electrolysis Cells (SOFC/SOEC), and Proton-Exchange Membrane Fuel Cells (PEMFC).

Replication Potential: Strategically designed for extension into additional high-growth sectors, including battery electrodes, catalytic materials, and additive manufacturing (AM).

Market Segment	Current (USD)	Projected Value (USD)	CAGR	Key Source
Materials Informatic (global)	148M (2024)	410M (2030)	19.2%	MarketsandMarkets
Materials Informatics (global, long-term)	208M (2025)	1,314M (2035)	20.22%	Precedence Research
Materials Informatics (Europe)	46.5M (2024)	309M (2034)	20.9%	Precedence Research
Construction Materials (global)	1.6T (2023)	2.5T (2030)	6.7%	Research and Markets
Sustainable Construction Materials	301.6B (2024)	NA	11.9%	GlobalData
Green Building Materials	285.9B (2024)	458.6B (2030)	8.5%	Grand View Research
Fuel Cell Market (global)	5.66B (2025)	18.16B (2030)	26.3%	MarketsandMarkets
PEMFC Market (global)	5.68B (2025)	27.23B (2033)	22.4%	Grand View Research
Hydrogen Fuel Cells (Europe)	2.35B (2025)	NA	NA	MarketDataForecast

Exploitation Models for KER#01 (Open Repository)

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The platform is offered as a cloud-based SaaS with a **tiered freemium pricing structure**: a free basic tier lowers the adoption barrier, while two more priced tiers provide progressively advanced industrial features and services.

1. Open and Community-Driven Layer

Free access to public datasets, documentation and scientific outputs with the objective of dissemination, visibility and community growth

2. Service-Based Exploitation

Subscription or pay-per-use access to advanced storage and compute services, Secure industrial data spaces and Enhanced analytics and workflow support

3. Consultancy and Integration Services

Support to industry and R&I actors for system integration with internal R&D environments and data governance, interoperability and AI readiness

- ✓ Follow-up EU projects
- ✓ Additional sources include other project grants, national and regional incentives, risk capital, private investment, and loans
- ✓ R&D investment portfolio of the company leader or other relevant stakeholders

Thank you!

MatCHMaker
Materials Characterisation & Modelling

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