University of Naâma

Will AI Reinvent Mechanics?

Scientific Challenges and Research Opportunities

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Presentation

Main Functions

- **Teacher-Researcher at UDL-SBA**
- Director of EEDIS research laboratory
- Head of HPC center : (High Performance Computing)

Institutional Involvement

- Member of the **Incubator Scientific Council**
- Member of **TISC** (Technology and Innovation Support Center)
- Member of the **House of AI**
- Head of doctoral training program

A question for you...

Is AI a threat or an opportunity ?

Sommaire

1 Introduction

2 AI Fundamentals
- Definition of Artificial Intelligence
- Historical Evolution of AI
- AI Subdomains

3 Generative AI
- Definition and Technologies
- Impact and Applications

4 The Great Shift

5 The Three Ongoing Revolutions
- 1st Revolution : Custom Materials
- 2nd Revolution : Cognitive Manufacturing
- 3rd Revolution : Resilient Cyber-Physical Systems

6 The Major Research Challenges

7 Conclusion

2 AI Fundamentals

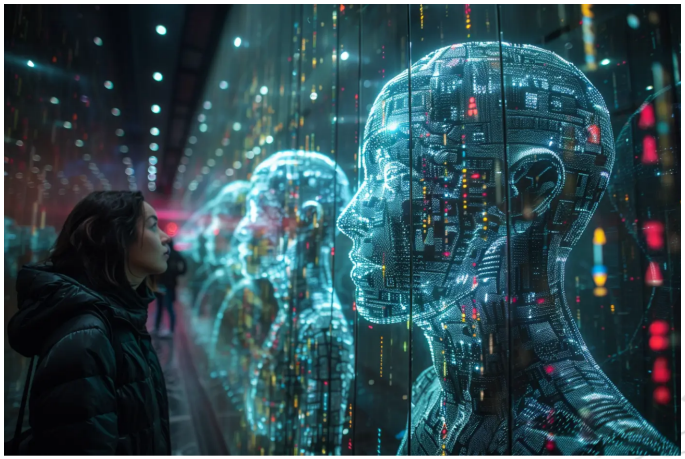
- Definition of Artificial Intelligence

What is Artificial Intelligence ?

Definition

AI refers to the set of theories and techniques developing computer programs capable of simulating human intelligence.

- **Cognitive abilities** : Learning, reasoning, perception, decision-making
- **Objective** : Create machines that perform well on tasks requiring intelligence
- **Approaches** : Symbolic, connectionist, computational



2 AI Fundamentals

- Historical Evolution of AI

Major Milestones of AI

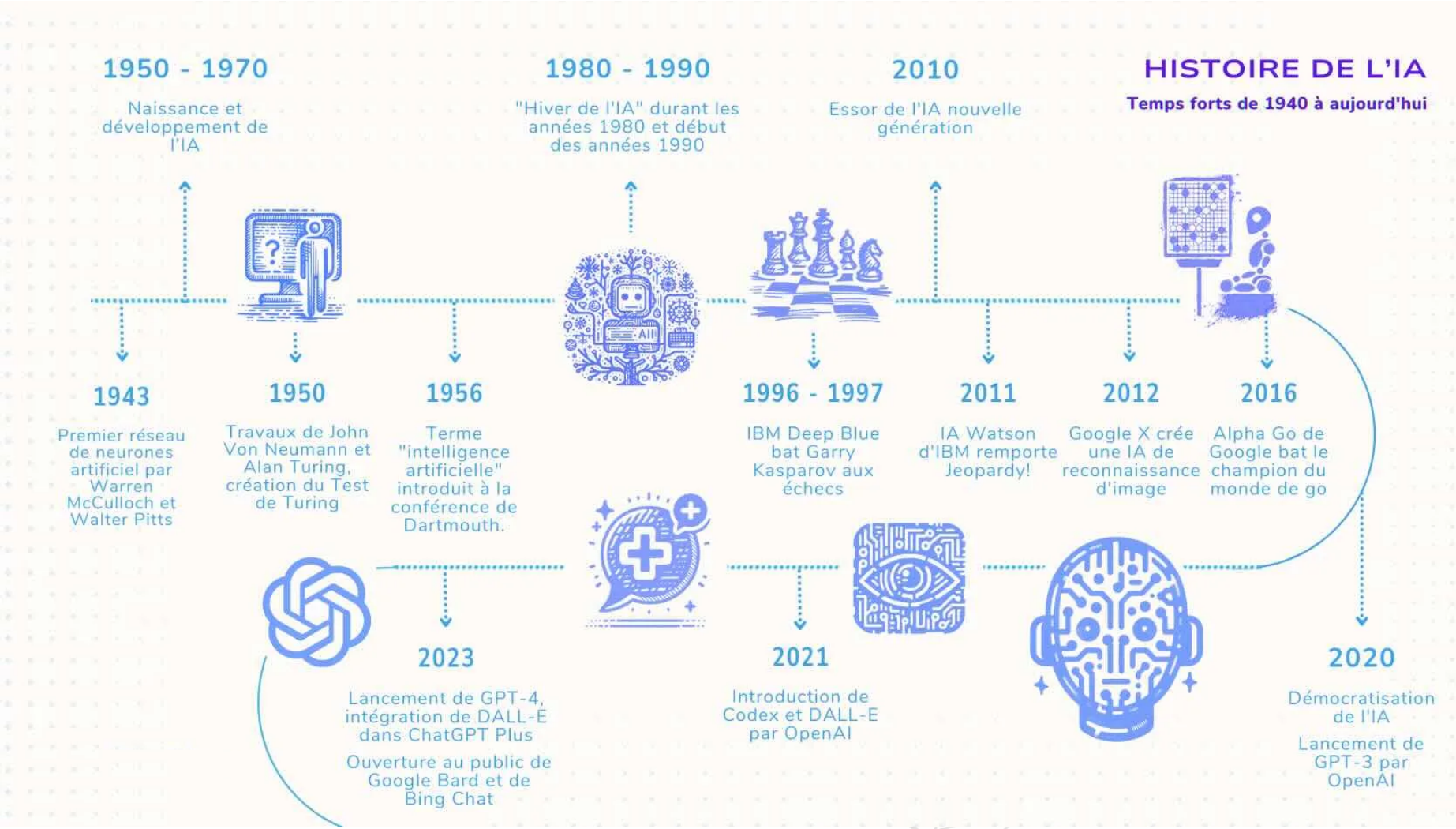


Figure – Chronological evolution of AI

2 AI Fundamentals

- AI Subdomains

Main AI Domains

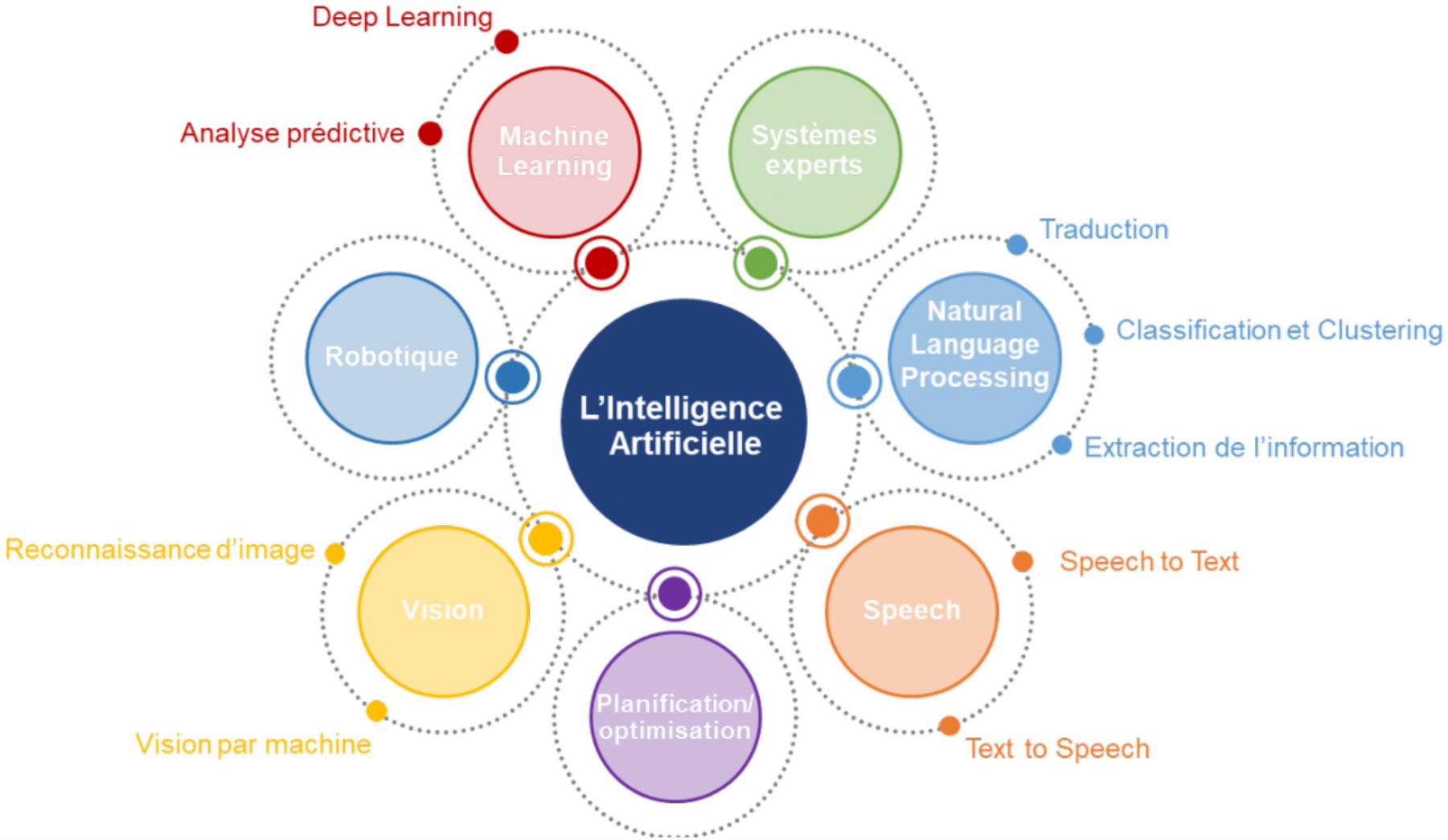


Figure – Interconnection of AI domains

3 Generative AI

- Definition and Technologies

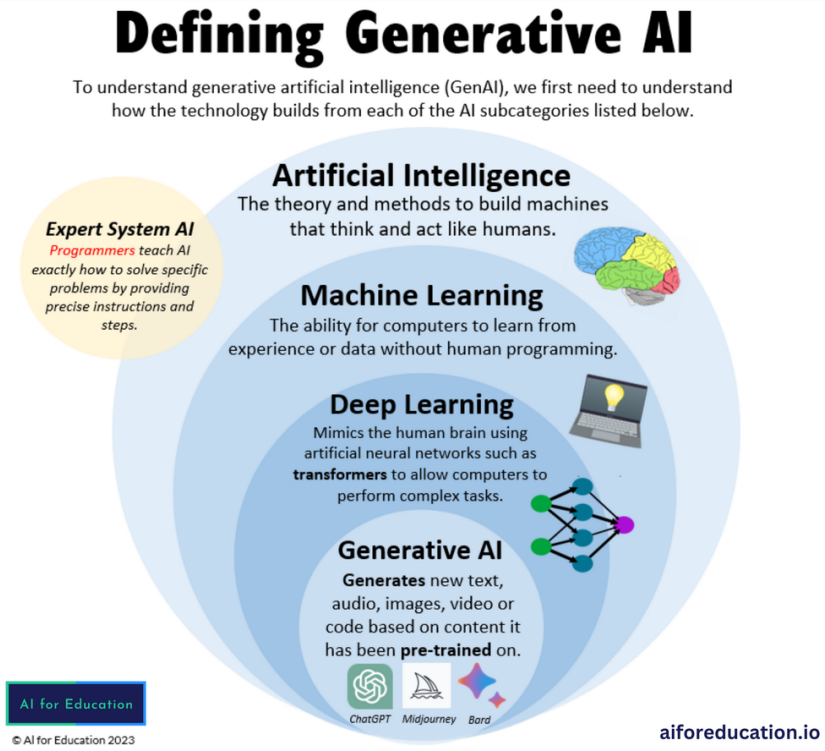
Generative AI : Creative Revolution

Definition

Generative AI creates new content (text, images, music, code) rather than analyzing or classifying existing data.

Key Technologies :

- Language models (GPT, LaMDA)
- Generative Adversarial Networks (GANs)
- Diffusion models (DALL-E, Stable Diffusion)
- Variational autoencoders



3 Generative AI

- Impact and Applications

Contributions to AI Adoption

Adoption Accelerator

Generative AI has democratized access to AI thanks to :

- **Accessible interfaces** : Intuitive conversational chatbots
- **Tangible applications** : Concrete and visible results
- **Reduced technical barriers** : No longer need advanced technical expertise
- **Augmented productivity** : Measurable gains in various sectors
- **Mass personalization** : Adaptation to individual needs

Attention

Need for ethical regulation and human validation

Retrieval-Augmented Generation (RAG)

- Combines a generation model (LLM) with a search module.
- Allows integration of updated external knowledge.
- Reduces hallucinations and improves answer accuracy.
- Typical approach :
  1. Document indexing
  2. Retrieval of relevant passages
  3. Generation of enriched response

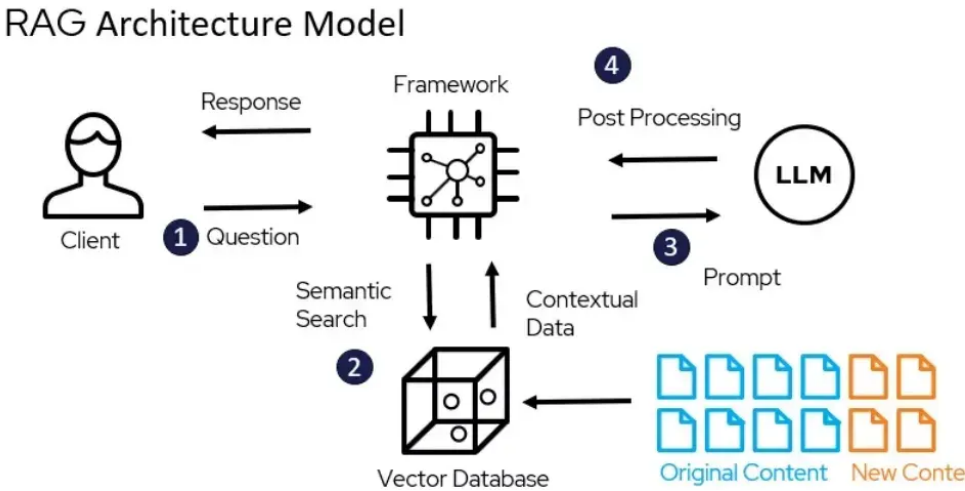


Figure – Simplified RAG pipeline diagram

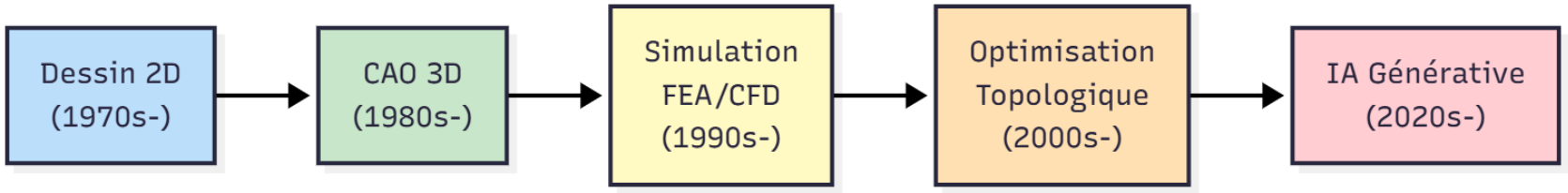
Generative AI Applications

Application Domains

- Content creation (texts, articles)
- Design and digital arts
- Software development (code generation)
- Scientific research (molecule discovery)
- Personalized marketing
- Education (Education 4.0)
- Industry (Industry 4.0)
- Mechanics (Digital twins)

Figure – Generative AI in digital twins

Historical Evolution of Tools in Mechanics



Exponential Acceleration

Each technological leap has externalized a growing share of the cognitive load :

CAD : Externalization of technical drawing

Simulation : Externalization of validation

Optimization : Externalization of improvement

AI : Externalization of **discovery**

Paradigm Shift : From "Trial and Error" to Conceptual Exploration

Old Paradigm

Linear Sequential Design

1. Initial design
2. Numerical simulation
3. Physical prototyping
4. Experimental testing
5. Manual iterations

Limitations :

- Limited design space
- High time cost
- Locally optimal solutions

New Paradigm

Algorithmic Exploration

1. Constraint definition
2. AI exploration
3. Concept generation
4. Multi-scale validation
5. Global optimization

Advantages :

- Expanded design space
- Counter-intuitive solutions
- Multi-objective optimization

5 The Three Ongoing Revolutions

- 1st Revolution : Custom Materials

1st Revolution : "Custom" Materials

Fundamental Transition

From : "Which material in the catalog ?"

To : "Which material should I create for my application ?"

"Impossible" Alloys

Approach :

- ML on crystalline databases
- Prediction of stable phases
- Compositional optimization

Results :

- High-entropy alloys
- Superalloys stable at 1200℃+

Smart Metamaterials

Approach :

- Neural networks for microstructures
- Multi-scale topological optimization

Properties :

- Programmable damping
- Negative stiffness
- Controlled non-linear behavior

Adaptive Composites

Approach :

- Fiber/matrix architecture optimization
- Multi-physical behavior prediction

Applications :

- Aerospace structures
- Lightweight automotive parts
- Biomedical

Concrete Example : Metamaterial Design by AI

Design Process

1. **Goal definition :**
   - Target Young's modulus
   - Maximum density
   - Manufacturing constraints
2. **AI exploration :**
   - Generative algorithms
   - Generative Adversarial Networks (GAN)
   - Bayesian optimization
3. **Multi-scale validation :**
   - Homogenization simulation
   - Virtual testing
   - Targeted prototyping

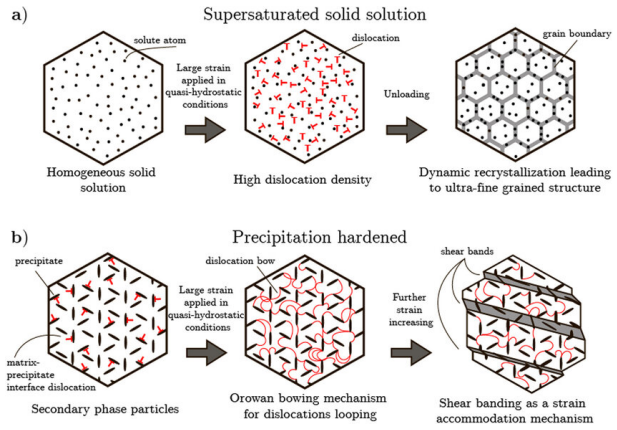


Figure – Microstructure evolution

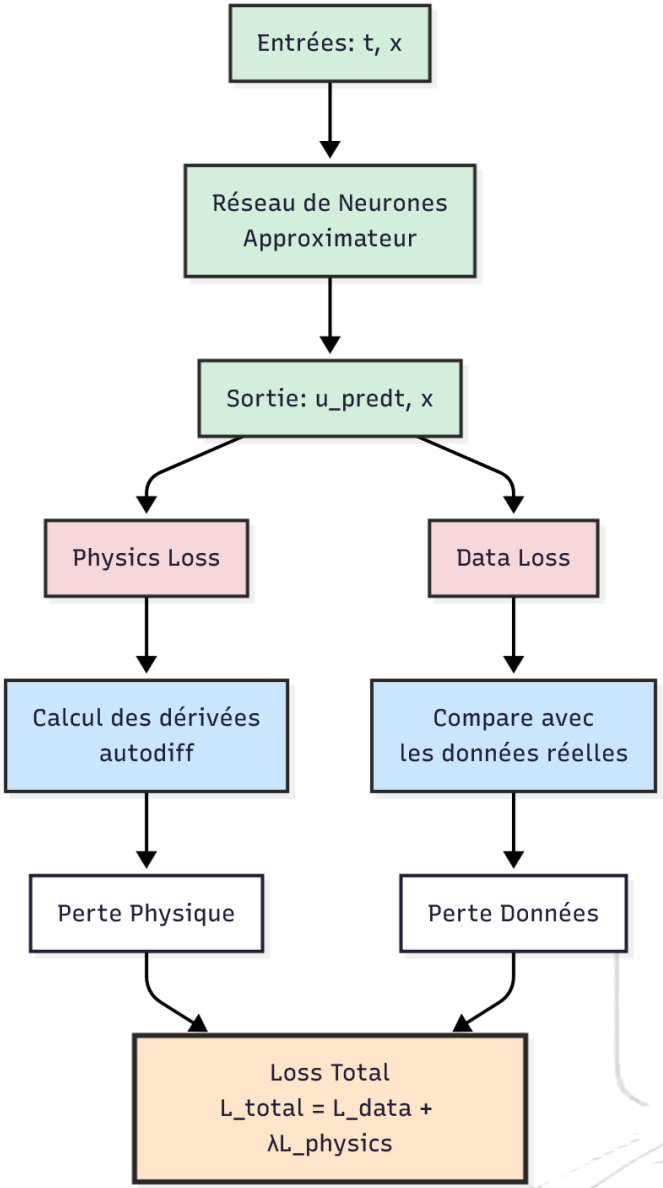
Performance Gain

- High stiffness/density ratio
- Reduced design time and cost

Physics-Informed Neural Networks (PINNs)

- A Physics-Informed Neural Network (PINN) is a type of neural network that learns to solve a problem (like predicting temperature in a room) not only from measured data but also by respecting the physical laws governing the system.
- A PINN is a machine learning framework designed to solve regression and partial differential equation (PDE) problems. Its main innovation is to directly integrate physical laws (often formulated as PDEs) into the neural network's loss function.

Physics-Informed Neural Networks (PINNs)



Physics-Informed Neural Networks (PINNs)

Imperial College London

- Physics-Informed Neural Networks (PINNs) - An Introduction - Ben Moseley | Jousef Murad : https ://www.youtube.com/watch ?v=G_hIppUWcsc
- https ://github.com/benmoseley/harmonic-oscillator-pinn-workshop
- https ://benmoseley.blog/my-research/so-what-is-a-physics-informed-neural-network/
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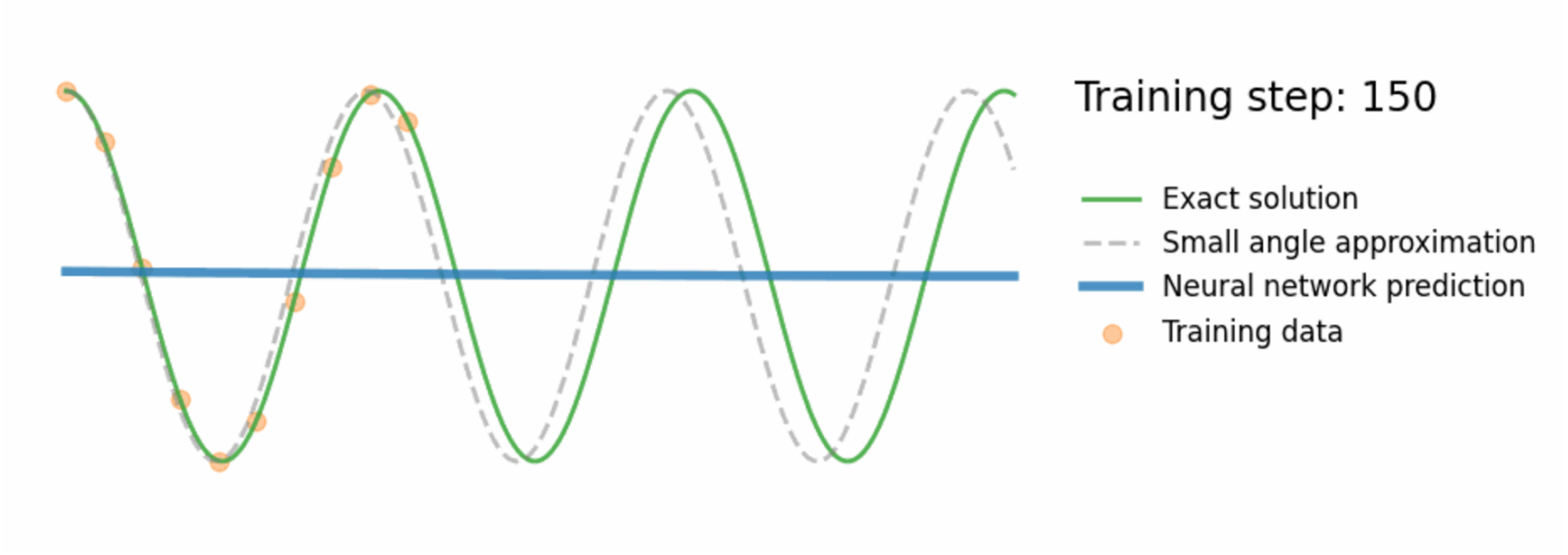
Physics-Informed Neural Networks (PINNs)



Physics-Informed Neural Networks (PINNs) and Metamaterials

1. Md Mahmudul Hasan, Zekeriya Ender Eger, Arulmurugan Senthilnathan and Pinar Acar. "**Microstructure-Sensitive Material Design with Physics-Informed Neural Networks**," American Institute of Aeronautics and Astronautics. 2023-0539. AIAA SCITECH 2023 Forum. January 2023.
2. Shen, C., Zhao, H. & Jiao, J. A **multi-subnets physics-informed neural network (Ms-PINN) model for transient heat transfer analysis in materials with heterogeneous microstructures**. Engineering with Computers (2025). https ://doi.org/10.1007/s00366-025-02183-3
3. Duc Vinh Nguyen, Mohamed Jebahi, Francisco Chinesta. **Physics-informed neural networks as alternative to finite element solvers**. 26e Congrès Français de Mécanique, Laboratoire d'Etude des Microstructures et de Mécanique des Matériaux (LEM3 - UMR CNRS 7239), Aug 2025, Metz, France. ⟨hal-05313104⟩
4. Victorita Dolean, Alexander Heinlein, Siddhartha Mishra, Ben Moseley," **Multilevel domain decomposition-based architectures for physics-informed neural network**s",Computer Methods in Applied Mechanics and Engineering, Volume 429, 2024, 117116, ISSN 0045-7825, https ://doi.org10.1016/j.cma.2024.117116.

5 The Three Ongoing Revolutions

- 2nd Revolution : Cognitive Manufacturing

2nd Revolution : "Cognitive" Manufacturing

Definition : Cognitive manufacturing uses AI and analytics to create self-optimizing systems that mimic human cognitive abilities (learning, reasoning, decision-making). It integrates IIoT and advanced analytics to improve processes, efficiency, and quality in dynamic environments.

Key aspects :

- **AI and analytics :** AI, ML and advanced analytics
- **Self-optimizing systems :** Self-configuration, self-optimization and self-adaptation
- **Human-machine collaboration :** Integration of human intelligence and digital systems
- **Dynamic adaptability :** Flexibility in the face of complex and unpredictable situations
- **Real-time data :** Leveraging IIoT for in-depth analysis

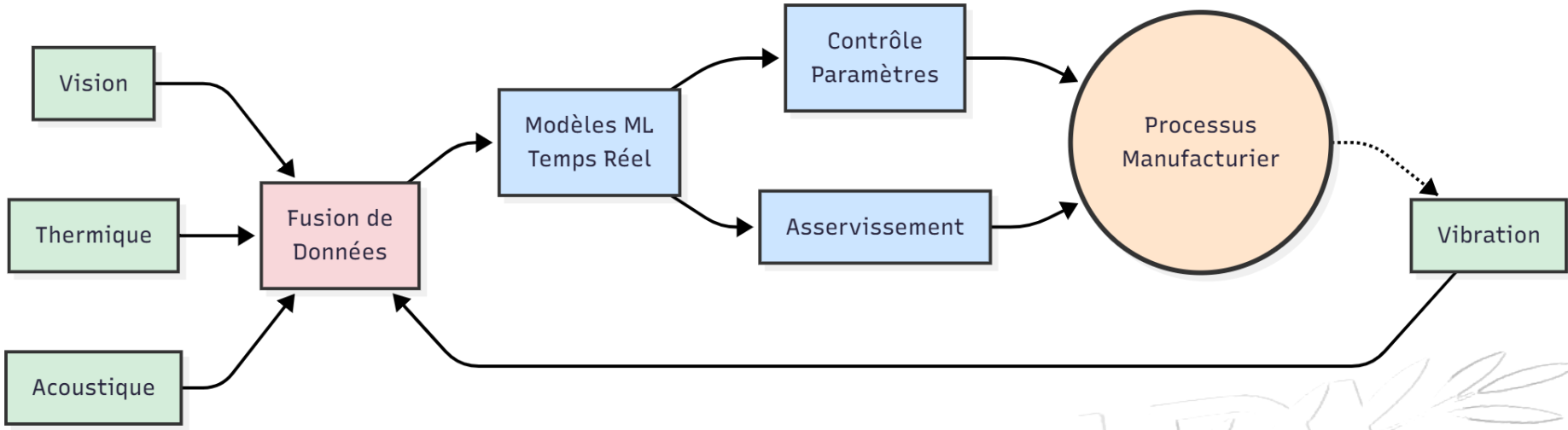
Advantages :

- Improved and faster decisions
- Increased efficiency and waste reduction
- Enhanced product quality
- Superior operational resilience
- Reduced downtime and costs

Architecture of a Cognitive Manufacturing System

Evolution of Production Systems

Automated → Connected → Intelligent → Cognitive



Industry 4.0 → Process 4.0 → Maintenance 4.0

2nd Revolution : "Cognitive" Manufacturing

Intelligent Additive Manufacturing

Multiple Sensors :

- High-speed cameras
- Infrared pyrometers
- Acoustic sensors
- Strain sensors

Adaptive Control :

- Real-time defect correction
- Layer-by-layer parameter optimization
- Final quality prediction

Advanced Adaptive Machining

Embedded Intelligence :

- Tool wear detection
- Thermal compensation
- Adaptation to actual part

Cognitive Robotics :

- Learning by demonstration
- Optimal trajectory planning
- Fluid human-robot collaboration

"Cognitive" Manufacturing and AI/ML

Deep Learning for Manufacturing

- https ://github.com/sumitsinha/Deep_Learning_for_Manufacturing/blob/master/README.md
- examples : https ://gi-thub.com/sumitsinha/Deep_Learning_for_Manufacturing/tree/master/assembly_eda_studies

Using ML To Solve Problems For A Manufacturing

- Using ML To Solve Problems For A Manufacturing Company : Richard Aragon : https ://www.youtube.com/watch ?v=P02Szb0PcnU
- code :https ://co-lab.research.google.com/drive/1H1K4Cm9pUPtdoMpMCON8QzFgK_stHc7_ ?usp=sharing

Decision tree in predictive maintenance

- : https ://github.com/somjit101/Predictive-Maintenance-Industrial-IOT/blob/main/Decision_Tree.ipynb

2nd Revolution : "Cognitive" Manufacturing

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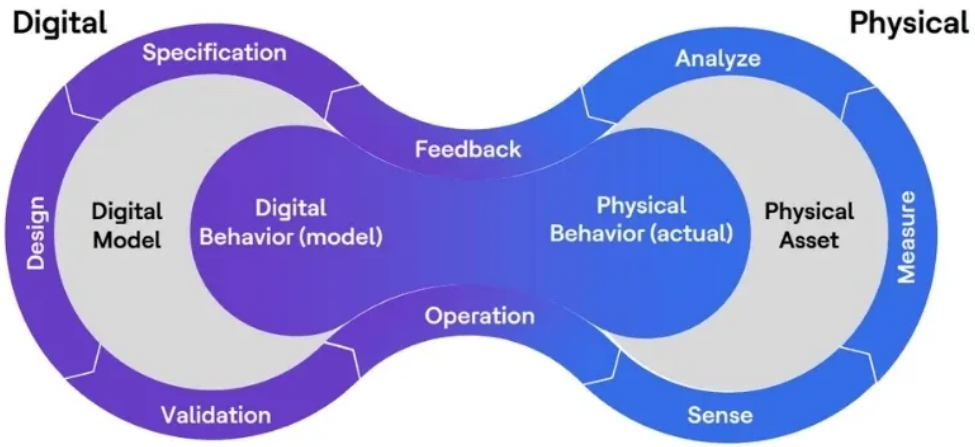
5 The Three Ongoing Revolutions

- 3rd Revolution : Resilient Cyber-Physical Systems

3rd Revolution : Resilient Cyber-Physical Systems



Evolution of the Digital Twin Concept

Static Twin : Initial design model (CAD)

Dynamic Twin : Updated with sensor data

Predictive Twin : RUL forecast with uncertainty

Adaptive Twin : Real-time self-reconfiguration

Cognitive Twin : Virtual replicas capable of understanding and reacting

3rd Revolution : Resilient Cyber-Physical Systems

Critical Applications

Aerospace :

- Engine life prediction
- Flight control reconfiguration
- Condition-based maintenance

Energy :

- Real-time wind turbine optimization
- Predictive grid management
- Maintenance scheduling

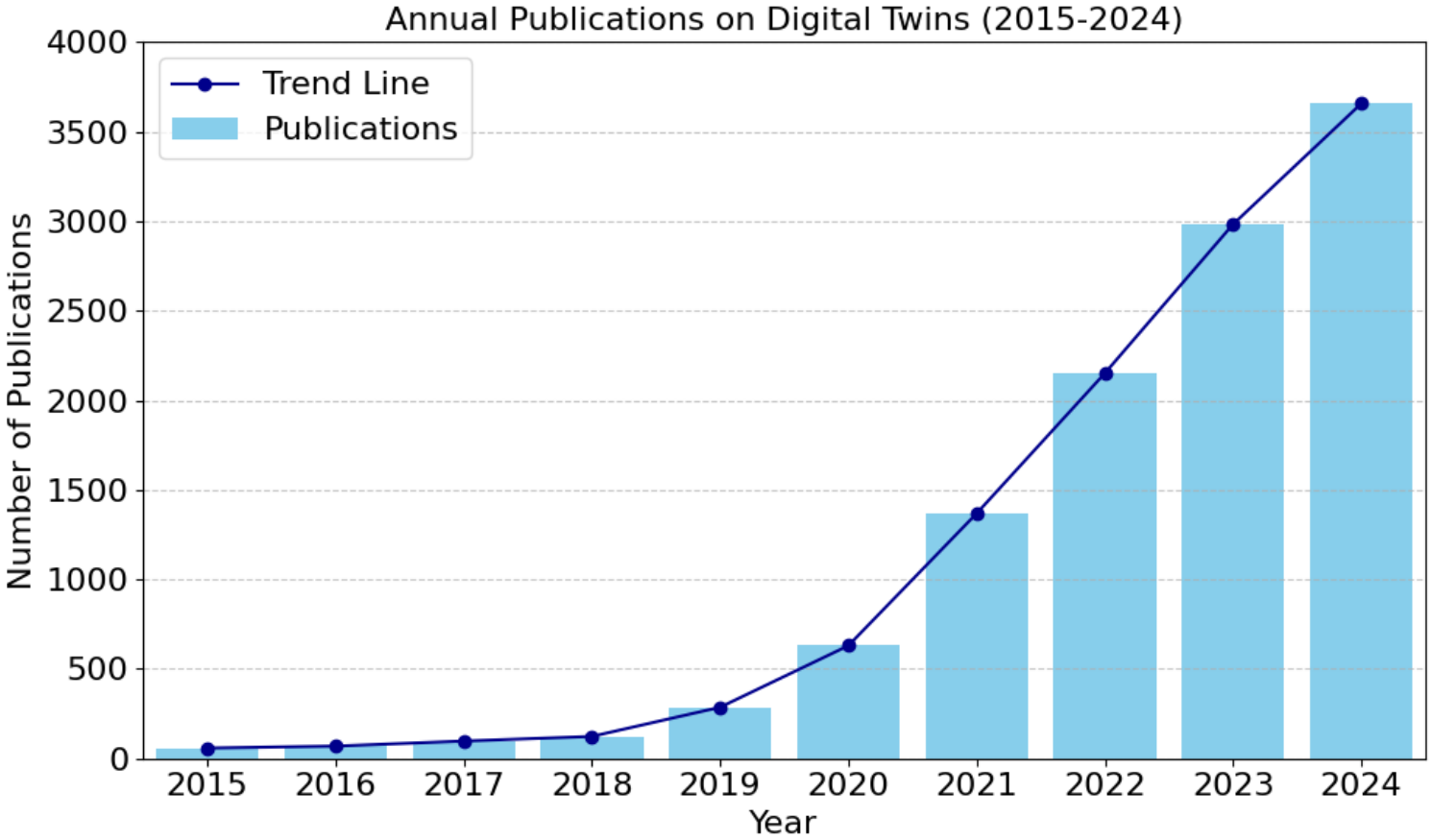
Measurable Advantages

- **Availability :** increased
- **Maintenance costs :** reduced
- **Consumption :** reduced
- **Safety :** Risk reduction
- **Durability :** Extended lifespan

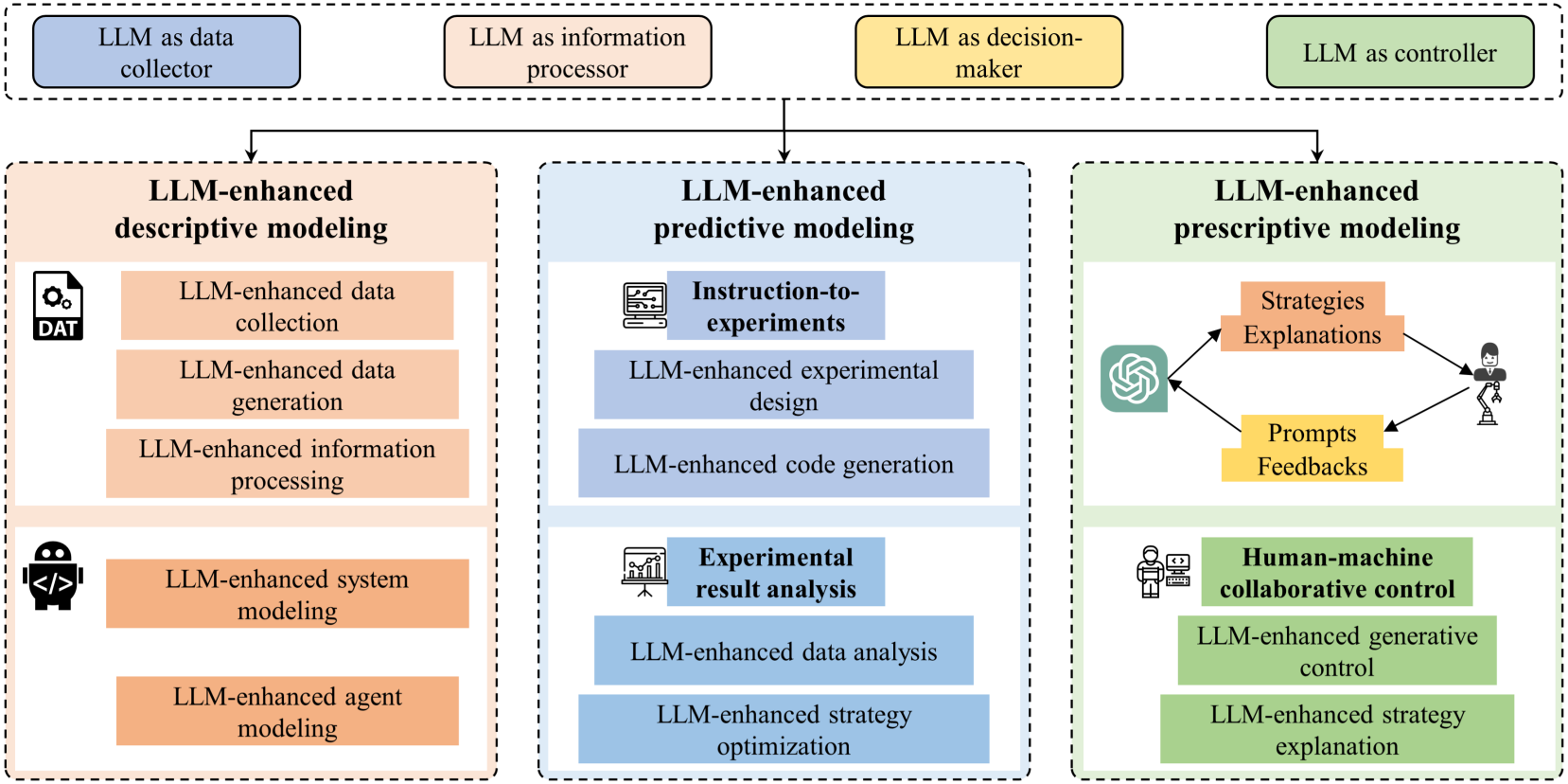
Key Innovation

Transition from **robustness** to **resilience**

3rd Revolution : Resilient Cyber-Physical Systems



3rd Revolution : Resilient Cyber-Physical Systems



Related Works

- Yangyang Liu, Tang Ji, Xiangyu Guo, Xun Xu, Jan Polzer, **A survey of cognitive digital twin and the potential use of LLMs,** Manufacturing Letters, Volume 44, Supplement, 2025, Pages 1242-1253, ISSN 2213-8463, https ://doi.org/10.1016/j.mfglet.2025.06.144.
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- Xirui Xiong, Hongming Cai, Han Yu, Bingqing Shen, Pan Hu,"**DR-RAG : Domain-Rule-based Retrieval-Augmented Generation for aviation digital model design**", Advanced Engineering Informatics, Volume 68, Part B, 2025, 103688, ISSN 1474-0346, https ://doi.org/10.1016/j.aei.2025.103688.

Synthesis : State of the Art and Trends

What is Mature

- Basic generative design
- Predictive maintenance
- Vision-based quality control
- Parametric optimization

In Active Development

- PINNs and hybrid models
- Cognitive digital twins
- Materials by design
- Adaptive manufacturing

Demo

Demonstration

Challenge Mapping

Data

Problems :

- Lack of labeled data
- High acquisition cost
- Source heterogeneity
- Privacy issues

Issues :

- Prediction quality
- Model generalization
- Reproducibility

Trust

Problems :

- Incomprehensible black box
- Uncertain robustness
- Certification difficulty
- Legal liability

Issues :

- Industrial adoption
- System safety
- Regulatory aspects

Skills

Problems :

- Rare dual competence
- Inadequate training
- Resistance to change
- Disciplinary silos

Issues :

- Continuous innovation
- Competitiveness
- Technological leadership

Challenge #1 : Strategies for Lack of Data

Technical Solutions

Synthetic Data :

- High-fidelity simulation
- Data augmentation
- Generative models (GAN, VAEs)

Transfer Learning :

- Generic physics pre-training
- Domain-specific fine-tuning
- Knowledge sharing

Active Learning :

- Selection of informative data
- Reduction of experimental costs
- Optimization of measurement campaigns

Organizational Solutions

Collaborative Platforms :

- Open data banks
- Exchange standards
- Data quality protocols

Existing Initiatives :

- Materials Genome Initiative
- European Materials Modelling Council
- NIST Data Resources

Question ? ?

Do we need a "GitHub" for mechanica data ?

Advantages vs. Intellectual property risks ?

Challenge #2 : Establishing Trust in AI Models

Explainable AI (XAI)

Techniques :

- Importance maps (LIME, SHAP)
- Counterfactuals
- Extracted rules
- Feature visualization

Applications :

- Understanding decisions
- Model debugging
- Physical validation

Physics-Informed Neural Networks

Principle :

- Integration of PDEs in loss function
- Respect for fundamental laws
- Reduced need for data

Advantages :

- Physically plausible solutions
- Improved extrapolation
- Increased confidence

Vision

Trust is **calculated** and **demonstrated**

Validation Framework

1. Rigorous cross-validation
2. Extreme scenario testing
3. Standardized benchmarks
4. Transparent documentation

Challenge #3 :Training Augmented Mechanical Eng.

New Skills Profile

Technical Skills :

- Classical solid mechanics
- Data science (Python, ML)
- Advanced numerical simulation
- Intelligent experimentation

Transversal Skills :

- Systemic thinking
- Interdisciplinary collaboration
- Technical communication
- Continuous learning

Research Strategies

Hybrid Teams :

- Mechanical engineers + Data Scientists
- Applied mathematicians
- Specialized computer scientists

Technological Platforms :

- Dedicated computing infrastructure
- Shared data banks
- Integrated workflow tools

Transformation of Training Programs

Progressive Integration :

- AI/ML courses in L3-M1
- Continuous teacher training
- Interdisciplinary projects

Call to Action

To Teacher-Researcher

Immediate Actions :

- Integrate ML into existing courses
- Launch interdisciplinary projects
- Train in domain-specific AI tools

Long Term Strategy :

- Develop dual skills
- Create shared platforms
- Establish quality standards
- Federate community

To PhD Students

Unique Opportunities :

- First mover decisive advantage
- Rare highly sought-after profile
- Multiplied research impact
- International career

Key Skills :

- Python and ML libraries
- Complex data analysis
- Critical thinking about AI
- Interdisciplinary communication

Your Role

You are the **architects** of tomorrow's mechanics

"Life is like riding a bicycle. To keep your balance you must keep moving."

Albert Einstein

La vie est comme faire du vélo. Pour garder votre équilibre, vous devez continuer à avancer.

Thank You!

Questions ! !

https ://github.com/boukli/Workshop_AI_Mechanical_Naama

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