



Al in support

of Interoperability

inter europe

innovation ∞ govtech ∞ community

Welcome!

Join us for an engaging and informative workshop session on 'AI for Interoperability'.

Workshop Objectives

Get inspired by the successes, challenges, and opportunities of our speakers in their **AI for Interoperability** journey and share yours!



Discover the importance of **Interoperability for the** development of high-quality AI solutions

Workshop Practicalities



On-site Participation

- Please silence your mobile devices
- The session is divided in **two parts** (9:00-11:00 and 11:30-13:00)
- A coffee break is planned at 11:00
- Wait for the **panel discussions** (at 10:15 and 11:15) for asking your questions
- A **microphone** will be passed by the moderators to ensure everyone can hear you
- We will be using **Slido for interactive questions** and polls



- The session is being live streamed
- Use Slido to ask questions and interact with the speakers during the panel discussions

All sessions are recorded



Wifi connection

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2: Al in support of Interoperability



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Part 1: Al for Interoperability





Workshop's speakers:









Use Cases in Finnish Public Administration

EIF: Layers of Interoperability

- IDEAL: "interoperability model" (IM), which is applicable to all digital public services, an integral element of the interoperability-by-design paradigm.
- TODAY: A concrete example of practical implementation of IM with LLMs in public sector service production
- Highlights challenges in a very legalist country

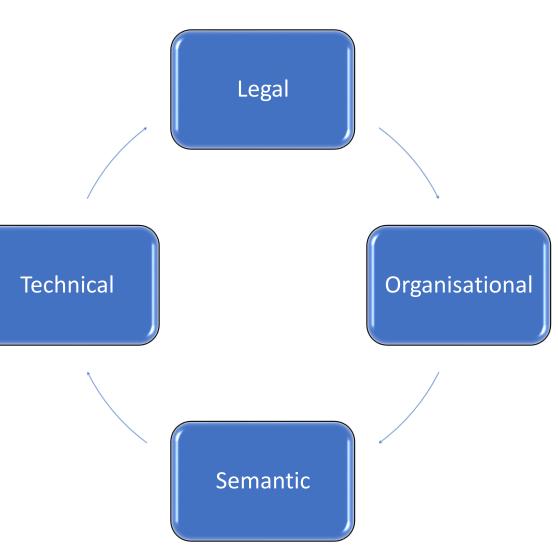
Interoperability model

pperability Governance



Interoperability in Design for Public Sector Services (Finland)

- In public services, legal interoperability comes first
- Requires sufficient expertise on the legal restrictions, examples:
 - Personal and sensitive information
 - The usage of data and extracted information
 - Security and safety
 - ... and the quality of outputs (cf. the problem of hallucination)



Layers of Interoperability: Legal

Legal considerations when using AI

- Rapidly developing technology with rapidly developing applications (lots of skepticism but also hype)
- No information that is confidential or personal data can or should be used as inputs
- Outputs should (must) be reviewed before being used
- Must avoid becoming dependent on a particular system (vendor lock-in)
- Soon: requirements from the AI Act (transparency, HRAI requirements, fundamental rights impact assessments, etc)

Use Case 1: Summarizing the results of a public consultation

- Public consultations are mandatory when negotiating and ratifying binding bilateral agreements
- A consultation can draw hundreds of opinions which must be analyzed and collected before the process can move on
- Generative AI can synthetize and summarize this material, including source tracking to determine which element of the summary originated from which opinion

Use Cases 2 and 3: Establishing legal context and 'regulatory metadata'

- Al can be used to examine a legal draft to determine other relevant legislation (both national and union level)
 - This helps consider implications for legal IO with any new initiative
- All new bills must contain a header section that details the sections and paragraphs that are to be modified (this can be simply or get very complex)
 - Complex, prone to human error, mistakes can have severe consequences
- Government AI pilots are underway to automate these processes using the Semantic Finlex dataset as training data

Eduskunnan päätöksen mukaisesti

muutetaan viranomaisten toiminnan julkisuudesta annetun lain (621/1999)

1 §:n 2 momentti, 4 §:n 1 momentin 4 ja 8 kohta, 11 §:n 4 momentti, 14 §:n 1 momentti, 24 §:n 1 momentin 17 ja 18 kohta, 33 §:n 1 momentti sekä 34 §:n 3 ja 6 momentti, sellaisina kuin niistä ovat 11 §:n 4 momentti laissa 385/2007, 14 §:n 1 momentti sekä 34 §:n 6 momentti laissa 495/2005, 24 §:n 1 momentin 17 kohta laissa 604/2018 sekä 33 §:n 1 momentti ja 34 §:n 3 momentti laissa 853/2020,

seuraavasti:

According to a decision by Parliament

in the Act on Openness of Government Activities (621/1999)

section 1 subsection 2, section 4 subsection 1, paragraphs 4 and 8, section 11 subsection 4, section 14 subsection 1, section 24 subsection 1 paragraphs 17 and 18, section 33 subsection 1 and section 34 subsections 3 and 6, as section 11 subsection 4 is in law 385/2007, section 14 subsection 1 and section 34 subsection 6 are in law 495/2005, section 24 subsection 1 paragraph 17 is in law 604/2018 and section 33 subsection 1 and section 34 subsection 3 are in law 853/2020

shall be changed as follows:

Semantic Finlex

- <u>Semantic Finlex</u> contains current legislation as open data in a machine readable format
 - Approx. 2800 regulations
 - Approx. 60,000 court decisions
- Built on top of Finlex, where all new legal instruments are published in an electronic format, as a research project
- For future applications, Finlex itself will be available as open data in MR format and through an API 'natively'

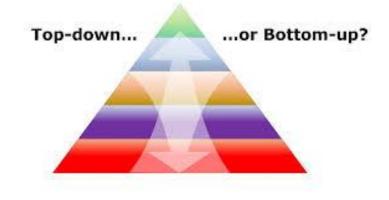
Use Case 4: Machine translation

- Finland has two official languages; every major proposal, bill, memorandum or new law must be available in both
- Proposals for new law should include a section on how the issue at hand has been tackled in other countries (usually similar countries like Sweden)
- Government machine translator Aura has been in use since September 2021
 - Trained using specialized datasets and specific vocabularies
 - Available to all central government civil servants
 - Translations from and to Finnish, English and Swedish
 - Up to May 2023, over 68 million words translated (~320,000 A4 sheets)

Layers of Interoperability: Semantic

Layers of Interoperability: Semantic

- TOP-DOWN: The development of standardised ontologies (SO) and taxonomies to create structured data
- The structured data + AI helps to "establish semantic interoperability between different systems"
- A "chicken-or-egg"- problem
- The data is often messy, noisy and fragmented, so you can't use SOs to establish interoperability



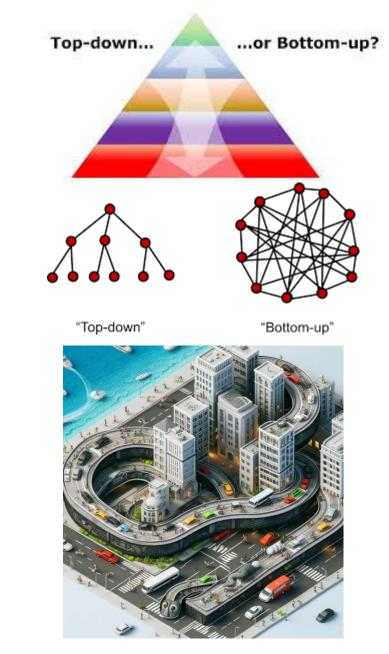
Artificial Intelligence for Interoperability in the European Public Se An exploratory st

Recommendation 4

Public administration should promote the use of uniform and standardised ontologies and taxonomies to create a common language and shared understanding of data that, combined with AI technology, can help in establishing semantic interoperability between different systems.

Layers of Interoperability: Semantic

- Bottom up & data driven approach: semantic interoperability "extracted" from messy data
- LLMs: potential to "extract" quasi-semantic structure from data,
- Words (text) in statistical "semantic" space
 - a representation of a item's statistical "meaning", while lacks functional meaning (Mahowald & al, 2023)
- Complementary to the top-down approaches (standard ontologies and taxonomies)
 - Interoperability by "prompting"



Source: Copilot, 20.2.2024

Layers of Interoperability: Technical

Layers of Interoperability: Technical (example: Pipelines)

- Problem for prompting (or any LLM)-based methods: LLMs: "stochastic parrots", tendency to extrapolate ("hallucinate") facts
- The degree of certainty for successful execution; an open question
 - A lot of misunderstandings concerning hallucinations
 - Different kinds of hallucinations (not all are legally relevant, cf. Wallenberg under review)
- Practical turn: Fine tuning and testing methods may, however, strengthen interoperability (or be disruptive)
 - If pipelines scalable -> increased efficiency
 - Disruptive cases: When pipelines don't work, case-bycase evaluation?

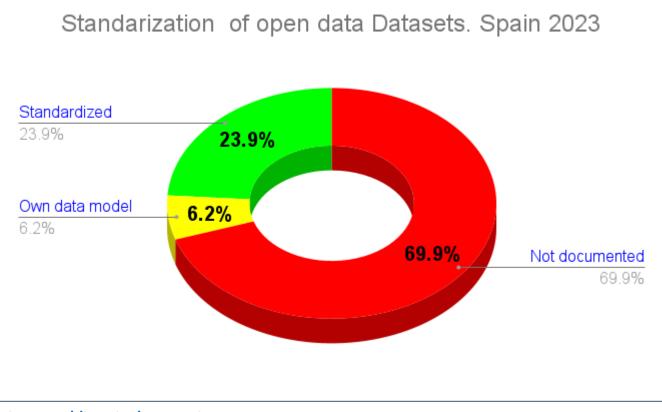




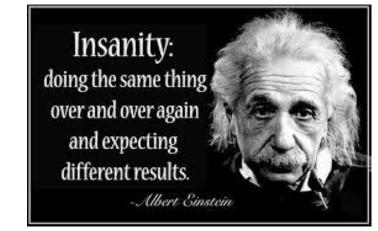
Thank you



Need standardized data models?



70% of 71.849 (2023) published datasets are not standardized

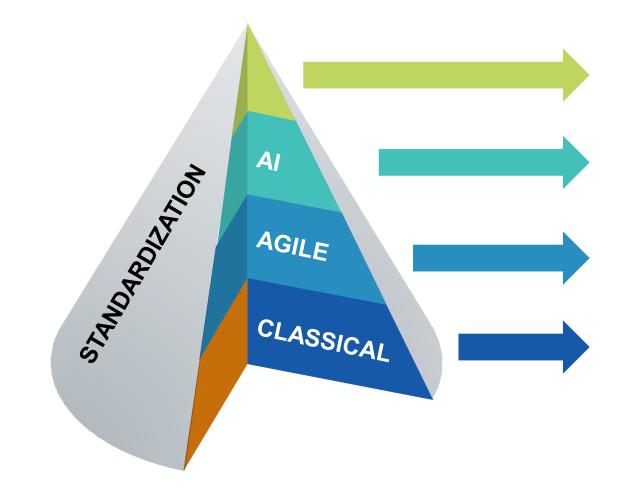


Classical standardization initiatives have got 80 datasets' data models in 6 years with low adoption

https://bit.ly/opendataspain2

023

Standardization on Al-age



FUTURE STANDARDIZATION

;;??

AI-SUPPORTED STANDARDIZATION (days)

Connected agents for standards Supported by AI agents

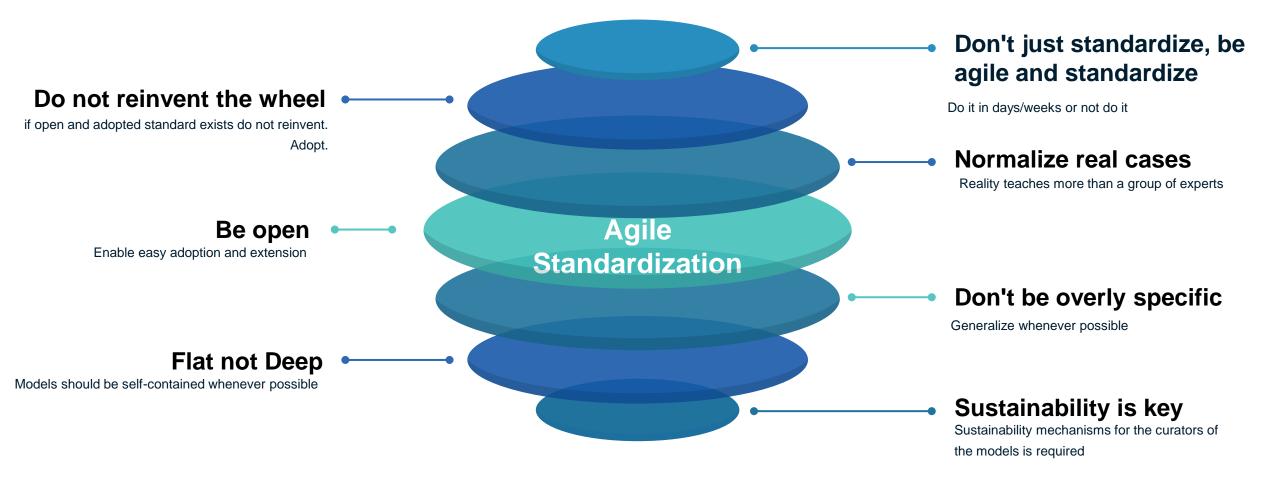
AGILE STANDARDIZATION (weeks)

Based on pioneers and in additive evolution Simple extension and evolution Open licensed

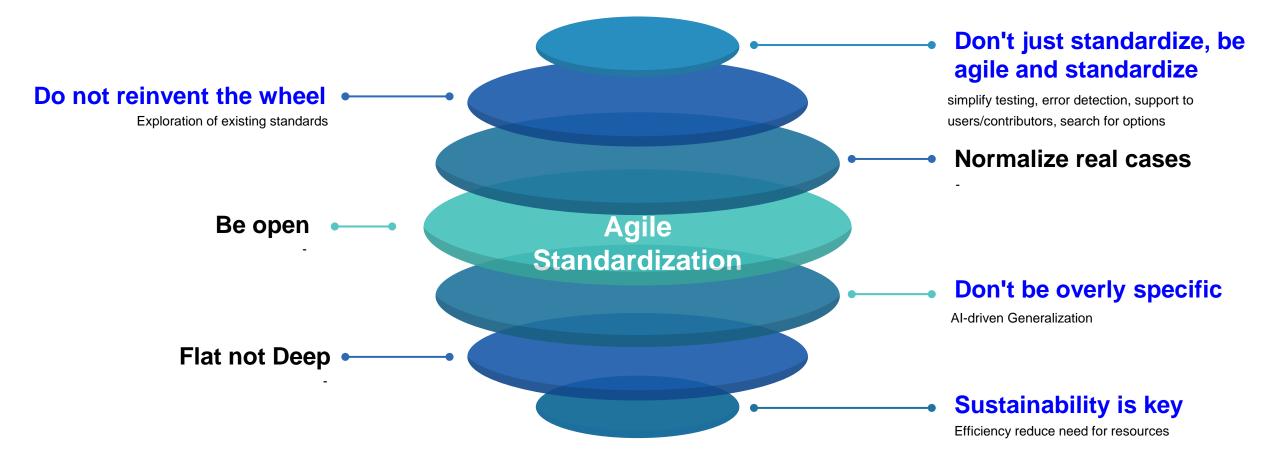
CLASSICAL STANDARDIZATION (Tenths months)

Based on consensus and stakeholders involvement Driven by standardization bodies Closed and rigid specifications

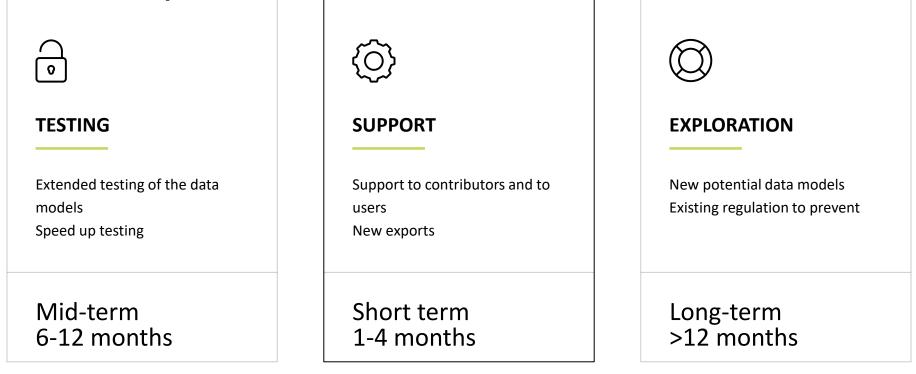
Seven best practices of agile standardization



With the help of Al



Expected benefits AI for standardization



Global aim: keep <1 week between first request and data model is published officially



Smart Data Models initiative

Stay in touch https://smartdatamodels.org



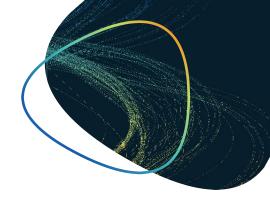


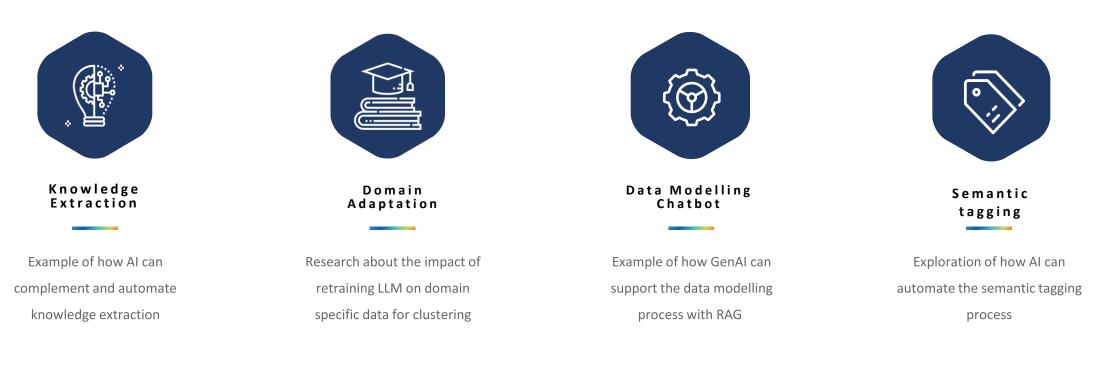
AI 4 Interoperability

Semantic interoperability and artificial intelligence as part of the SEMIC action

AI 4 interoperability

Empower interoperability through AI-driven solutions. Leverage advanced AI models to bridge data silos, foster collaboration, and drive innovation.







Knowledge Extraction

To harness the potential of AI at supporting interoperability (through automatic semantic alignment, vocabulary extraction, ontology extension, data modelling, ...), SEMIC has worked on building a proof-of-concept with DG GROW on the Transition Pathway for Tourism.

The objective was to see how to:

Extract topics from pledges

- Identify new topics emerging from the pledges
- Assign each pledge to its topic
- Analyse the coherence of existing topics

Extract results and implementation dates

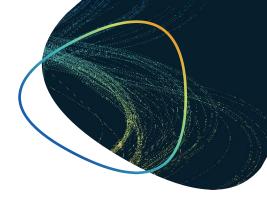
- Identify results mentioned in the pledges
- Identify implementation dates
- Build timeline of results





Extracting topics from a corpus of text...

Using **neural language models** and classical **clustering** tools, AI can automatically **identify the main topics** covered by a corpus of texts



GROW pledges Free-text



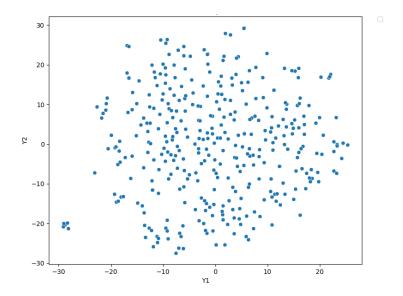
Extracting topics from a corpus of text...

Using **neural language models** and classical **clustering** tools, AI can automatically **identify the main topics** covered by a corpus of texts





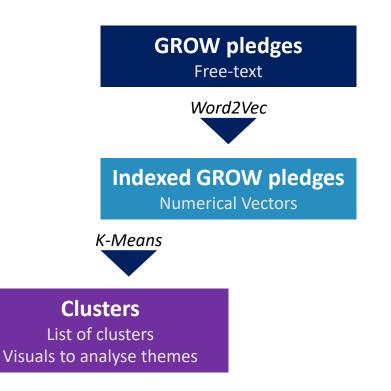
1) Word2Vec, a neural language model, allows to represent each pledge by a numerical vector while keeping all the semantic and syntactic information.



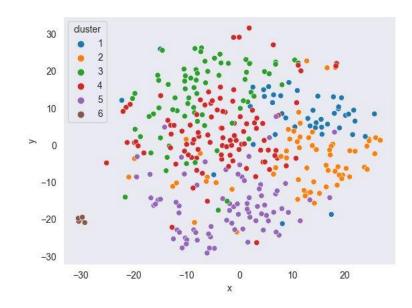


Extracting topics from a corpus of text...

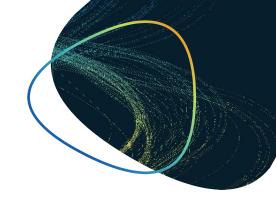
Using **neural language models** and classical **clustering** tools, AI can automatically **identify the main topics** covered by a corpus of texts



2) K-means, a clustering algorithm, allows to group pledges with a similar semantic meaning into different clusters

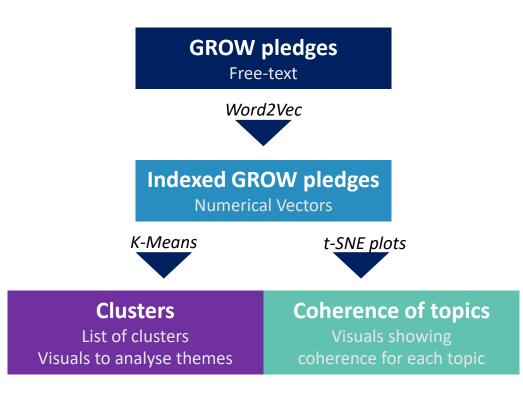




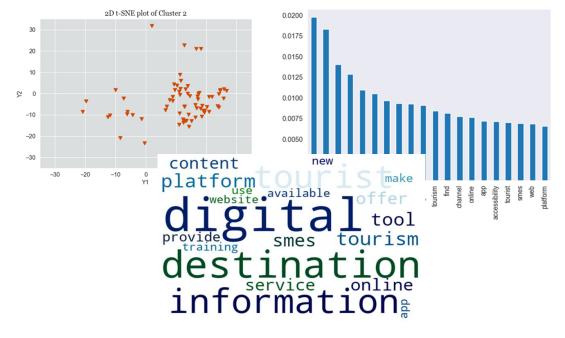


Extracting topics from a corpus of text...

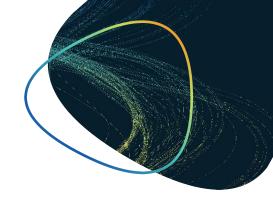
Using **neural language models** and classical **clustering** tools, AI can automatically **identify the main topics** covered by a corpus of texts



3) T-SNE plots and various word clouds allow to analyse the theme and coherence of the different topics.







Domain adaptation

To stay at the forefront of AI development, SEMIC has worked on developing analysis and research in the field of Generative AI. A study on the impact of domain adaptation was carried out on two state-of-the-art models:



How does the retraining of BERT on tourism data impacts the quality of pledge clustering?



How does the retraining of RoBERTa on tourism data impacts the quality of pledge clustering?



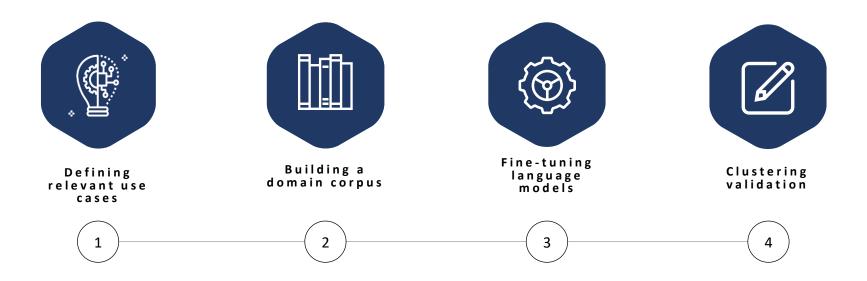


Context and research question

Recent research showed that providing Large Language Models with domain-specific data could significantly improve the performance of these AI models.

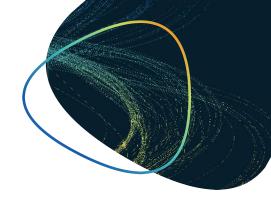
For instance, providing legal documents to the LLM could improve its ability to understand legal questions and respond to them more accurately.

Would it be beneficial to fine-tune language models on EU policy documents and legislations?





Extrinsic cluster validation: Results



	Extrinsic		
	Accuracy	F1-score	
Word2Vec	0.48	0.47	
BERT	0.22	0.25)
Fine-tuned BERT	0.29	0.34	
Roberta	0.21	0.19	
Fine-tuned Roberta	0.30	0.35	

Fine-tuning seems to have a positive impact on the accuracy of the clusters

Overall, the low accuracy and F1-score of the BERT and RoBERTa models tends to indicate that clusters created with these models are harder for "humans" to differentiate. In other words, the increase in complexity also decreased the usability of the results.

These conclusions may provide an interesting perspective on the **trade-off between using more sophisticated models and their usability**. While LLMs showed better quantitative results, they were also found to be less intuitive for human users. Hence, relying on more complex models may not always be the most valuable approach.





To support the work of data modellers, SEMIC has developed a prototype of chatbot that can **suggest classes, relations, and properties** to be added to a data model based on **existing concepts**.

Suggest a possible name for a class (CPSV-AP):

" a requirement fulfill a _____ " => autocomplete with "Rule"

Suggest a relation (Core Person):

"a person is ______ at this address" = (living, domiciliated, etc.)

Suggest properties (Core Business):

"by what a legal entity can be uniquely identified ?"

Examples of what the prototype could do

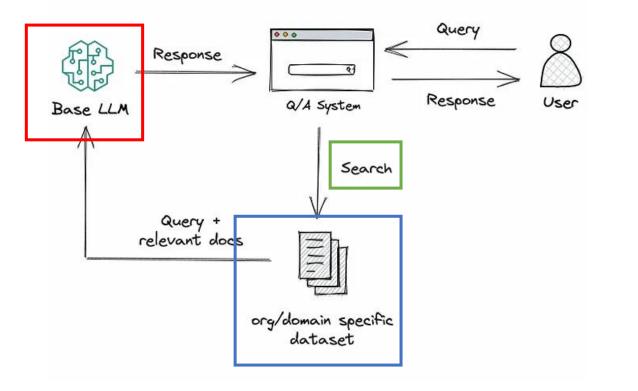




Retrieval augmented Generation

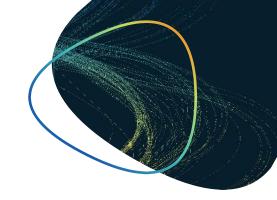
A Retrieval Augmented Generation (RAG) chatbot is based on three main building blocks:

Architecture of a RAG chatbot



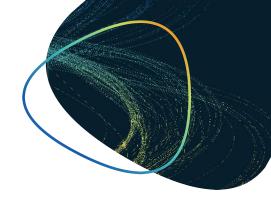
- **1) A pre-trained LLM:** A large language model trained on a very large corpus of generic data (e.g. Wikipedia).
- 2) A knowledge base: An index containing relevant documents for helping the data modeller, i.e., specification pages, RDF files, ...
- 3) A search engine: A tool able to search the knowledge base for the most appropriate documents to answer a user's query





Building a knowledge base

- Five relevant sources for CPSV-AP were identified, scraped, and chunked by the team.
- **Two existing RDF files** were identified as interesting sources.



Status	Data source	
\checkmark	<u>CPSV-AP</u>	-
\checkmark	CPOV	
\checkmark	CCCEV	
\checkmark	Open Data directive	
\checkmark	SDG regulation	
\checkmark	LOV	
\checkmark	Schema.org	

HTML pages containing relevant textual information about CPSV-AP (specification pages and regulations)

RDF files containing existing data models and concepts that could be reused by the chatbot

Building a RAG chatbot – Version 1

Suggest a relation (Core Person):

at this address" = (living, domiciliated, etc.) "a person is

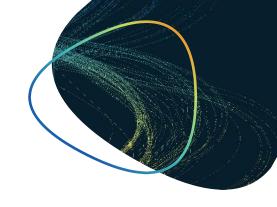
Suggest a possible name for a relation: a person is _____ at this address

Based on the retrieved documents, a possible name for the relation where a person is associated with an address could be "has address of the person" as indicated in ¹. This relation connects a person to their place of residence, business, or employer, and can also include an e-mail or internet address. Therefore, the complete phrase would be "a person is has address of the person at this address." However, this is a technical representation from the RDF schema perspective. In a more human-readable format, you might simply say "a person is located at this address" or "a person is resident at this address," depending on the context of the use case.

1 reference >

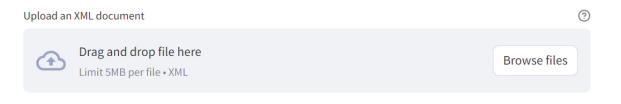
Use case 1:

Al-generated content may be incorrect



Building a RAG chatbot – Additional features





Model Bot

2

📴 Hello there! Upload an XMI document to start this session.

Your message

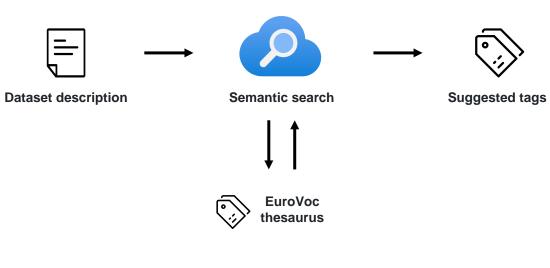




Semantic tagging

To facilitate the research and retrieval of documents on the European open data portal, SEMIC has explored how semantic tagging could be used to **suggest tags from the EuroVoc thesaurus** for a dataset.

High-level architecture:

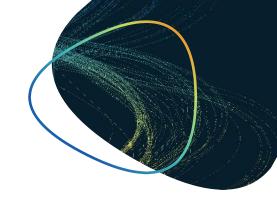






Data source

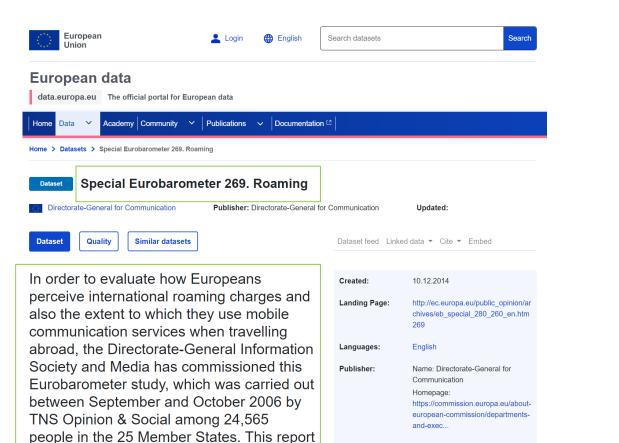
Starting from the different files available on the <u>OP portal</u> for Eurovoc, we found a zip file containing various XML files. One of those contains the definitions of the different Eurovoc tags in the different EU languages.

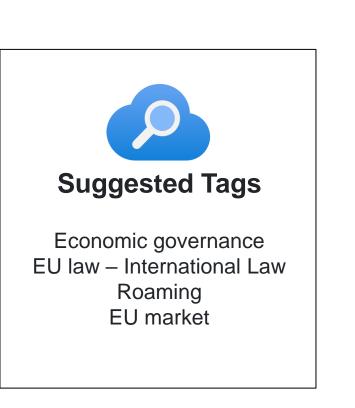




First results

Using Azure AI search explorer tool, we tested the efficiency of this approach for two examples. We used datasets found on the data.europa.eu.





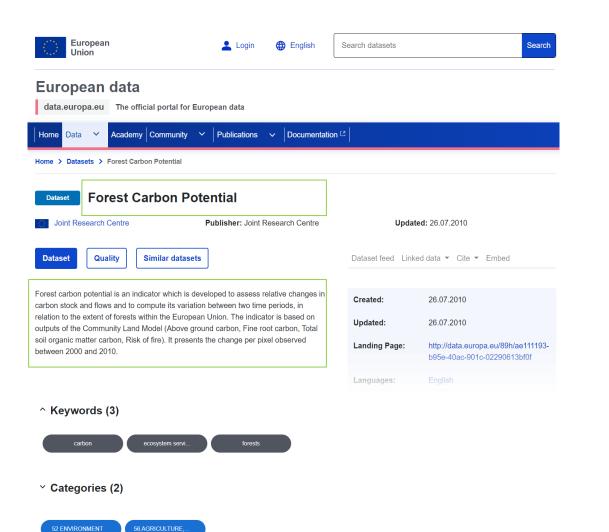
^ Keywords (5)

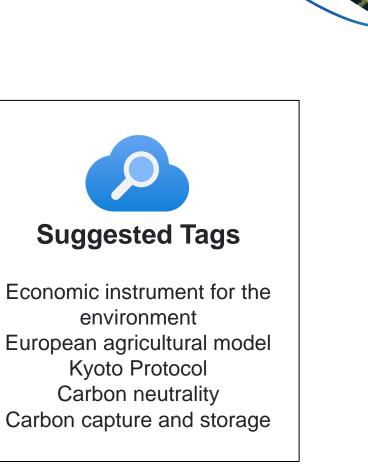


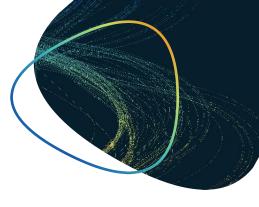


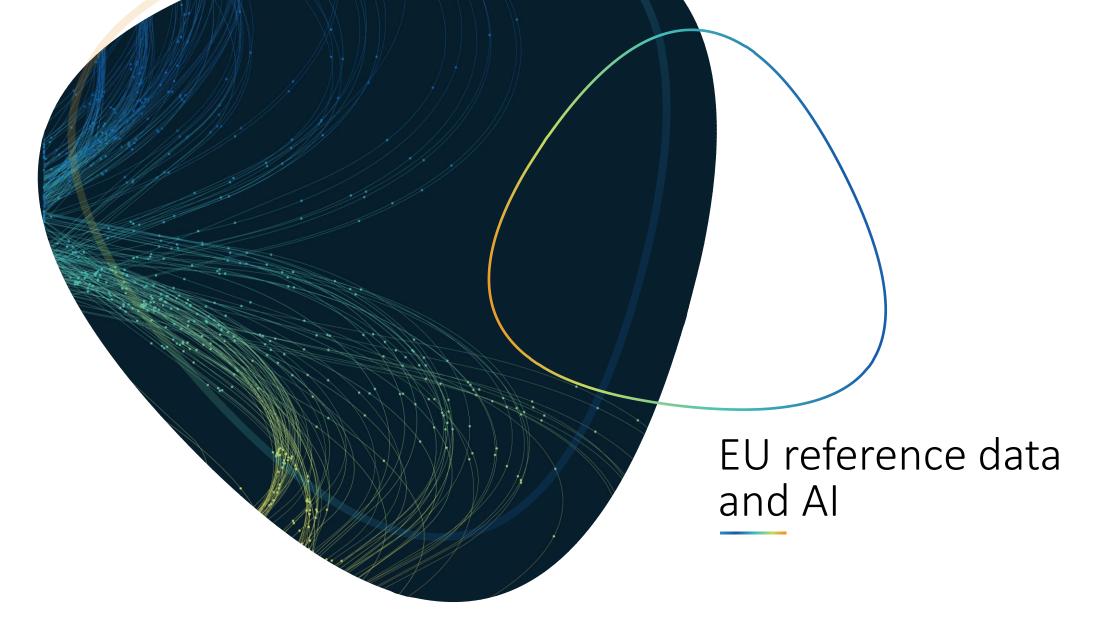
First results

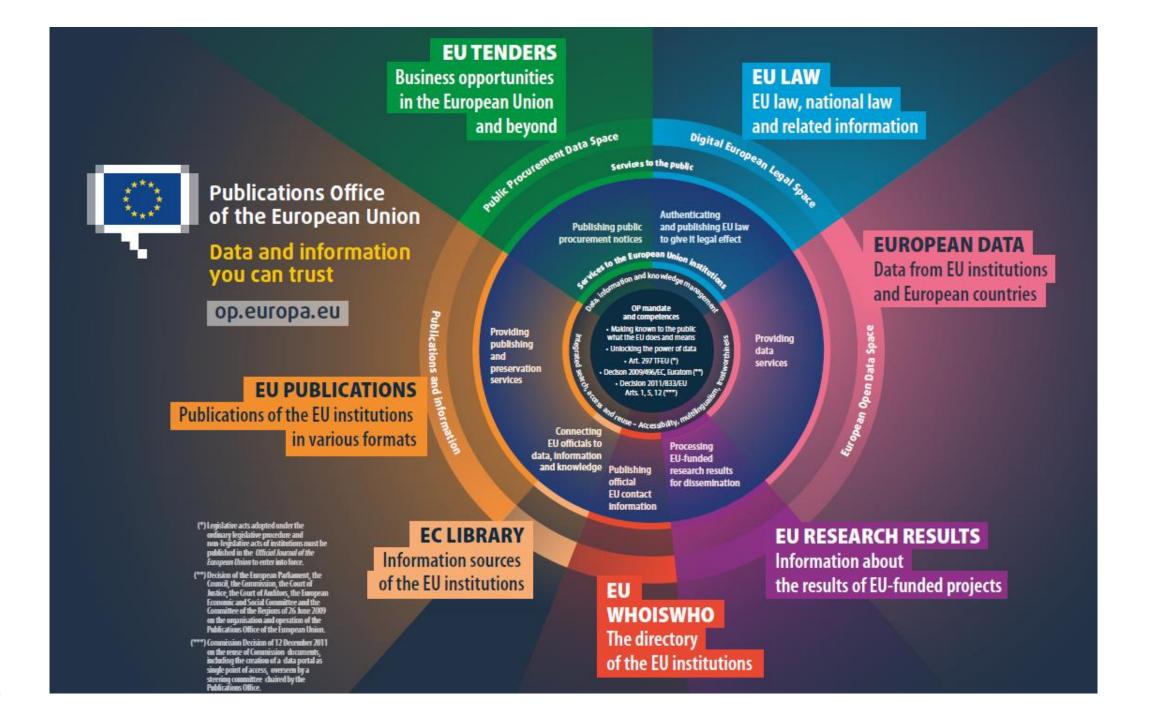
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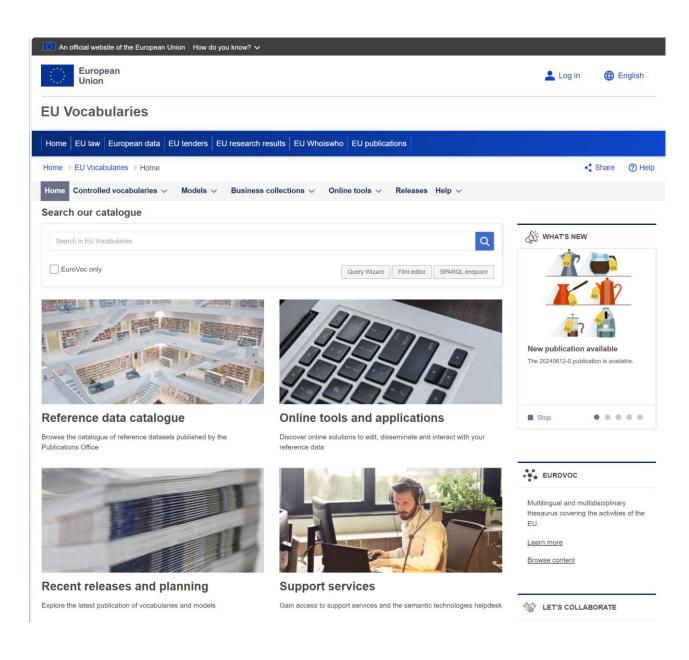




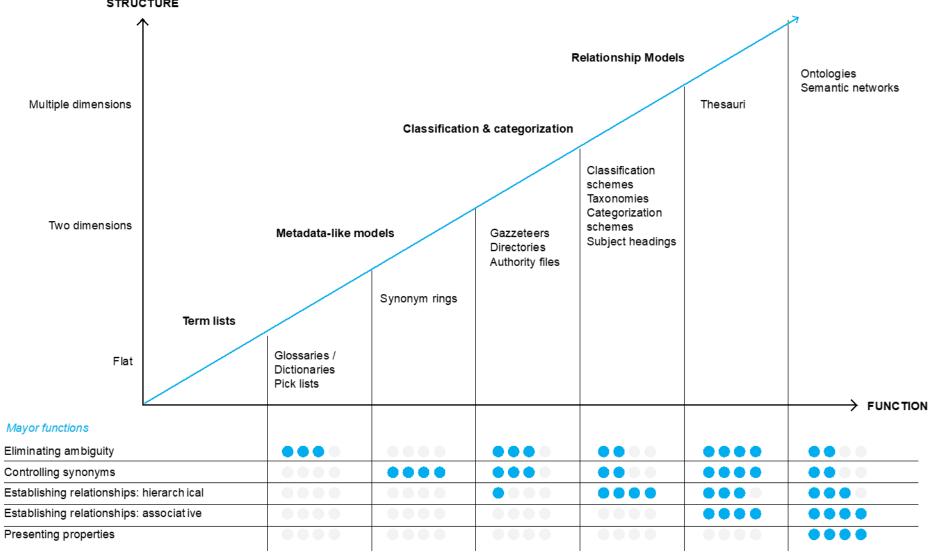




Central access to EU reference data



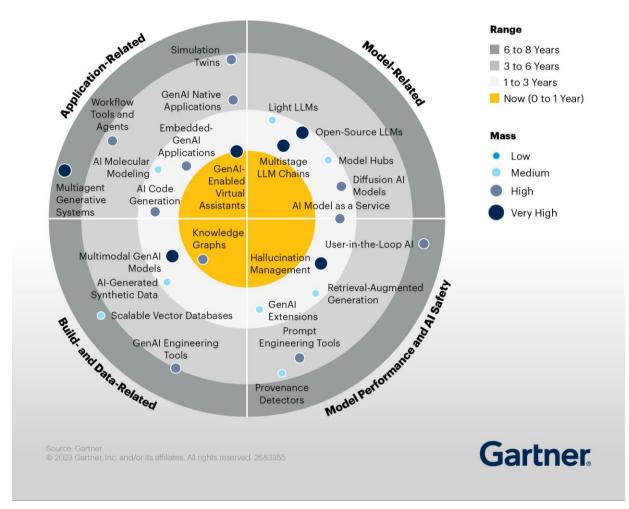
Different types of reference data



Do we need reference data in the era of AI?

- Trustworthiness of data
- Reference data allow to provide business context
- High-quality data needed to train, validate and test algorithms
- Data quality directly impacts performance and reliability of AI systems

Impact Radar for Generative AI



2024: Knowledge graph integration

Cons:

- Implicit Knowledge
- Hallucination
- Indecisiveness
- Black-box
- Lacking Domainspecific/New Knowledge

Pros:

- Structural Knowledge
- Accuracy
- Decisiveness
- Interpretability
- Domain-specific Knowledge
- Evolving Knowledge

Pros:

- General Knowledge
- Language Processing
- Generalizability

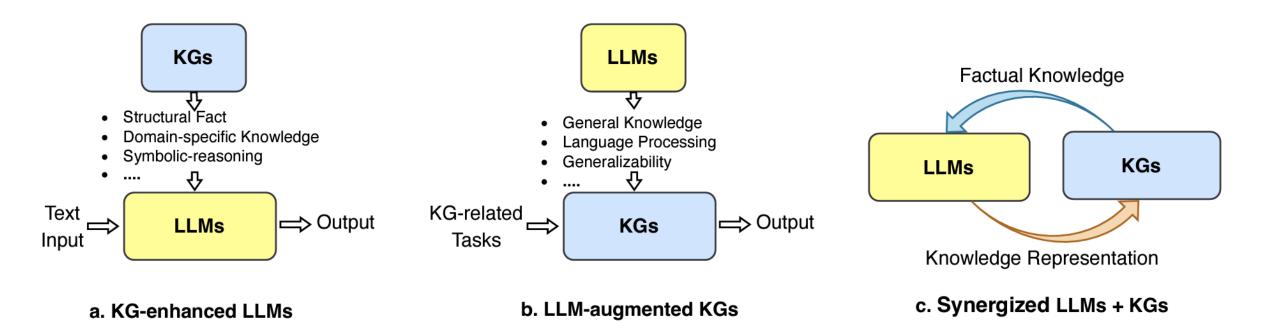
Cons:

- Incompleteness
- Lacking Language
 Understanding
- Unseen Facts

Large Language Models (LLMs)

Knowledge Graphs (KGs)

Knowledge Graph and LLM unification



Leveraging Generative Al for knowledge graphs (1)

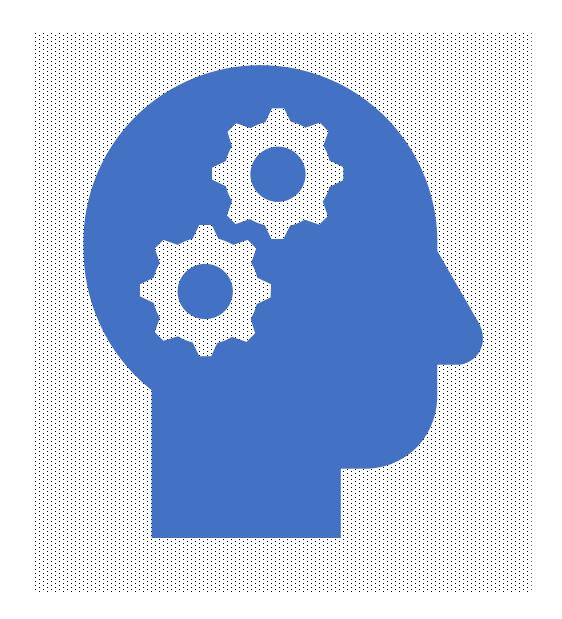
- Quality control and consistency checks
- Automated translation and multilingual alignment
- Automated vocabulary expansion
- Semantic analysis for vocabulary integration
- Custom vocabulary generation for specific needs

Leveraging Generative Al for knowledge graphs (2)

- Natural Language Processing for document tagging
- Chatbot for user interaction with reference data including query creation
- Enhanced search functionality including predictive text and autocomplete features
- Accessibility enhancements

Challenges and points for discussion

- Channel multitude of AI initiatives and share knowledge
- Automatic semantic tagging: From proof of concept to production
- What do you expect from EU reference data?





(d.)



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Panel Discussion



2: Al in support of Interoperability



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We have some questions for you too!





COFFEE BREAK 11:00-11:30 HALL 100





Part 2: Interoperability in support of Al



Workshop's speakers:



Building Trust In Al

Semantic Interoperability and Knowledge Graphs at the Rescue of Large Language Models

Agenda

- Introduction to the Trust Challenge
- Semantic Interoperability Explained
- Knowledge Graphs: Al's Trust Backbone?
- The ABI Project: What We Learned
- Impact on Trust and Efficiency
- The Future of Semantic AI



JEREMY RAVENEL

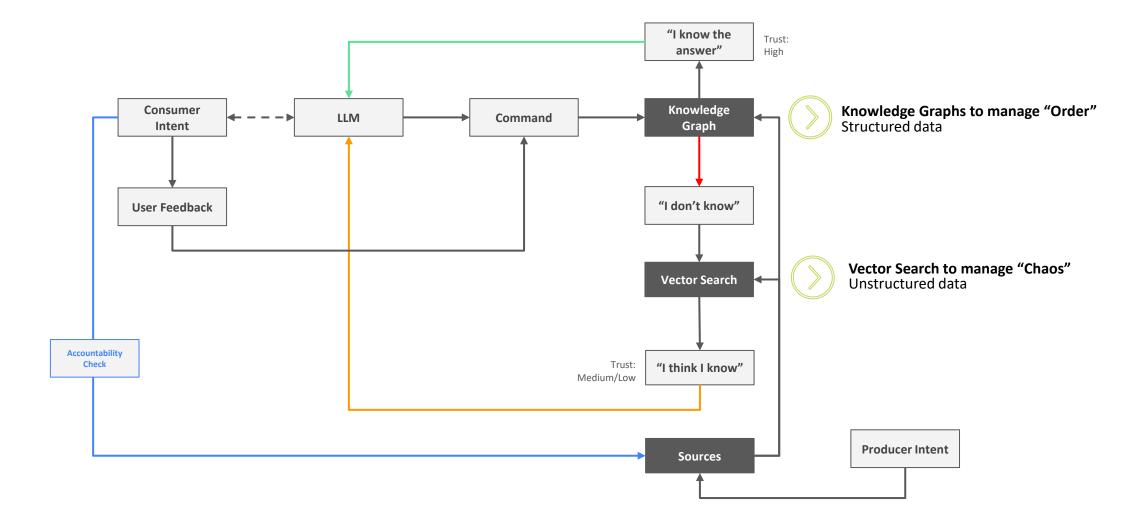
Founder & CEO

NaasAl

"I'm a farm boy turned data mercenary and now an entrepreneur, I'm passionate about practical innovation to make our digital lives less chaotic."



Large Language Models (LLMs) should not be trusted, they need to be integrated into a broader workflow to maximize their utility and ensure reliability.





SEMANTIC INTEROPERABILITY EXPLAINED

The Subtle Dance of Grounded AI Communication

Imagine semantic interoperability as the subtle dance of grounded AI communication, essential for ensuring clarity and precision. It's foundational for building a trusted AI ecosystem. It provides:

Common Language: Allows disparate AI systems to speak and understand each other

Enhanced Accuracy: Reduces misconceptions by providing clear data context

Facilitates Collaboration: Connects various sectors and organizations seamlessly

Supports Compliance: Aligns with regulatory standards for data usage and privacy

Knowledge Graphs: Al's Trust Backbone?

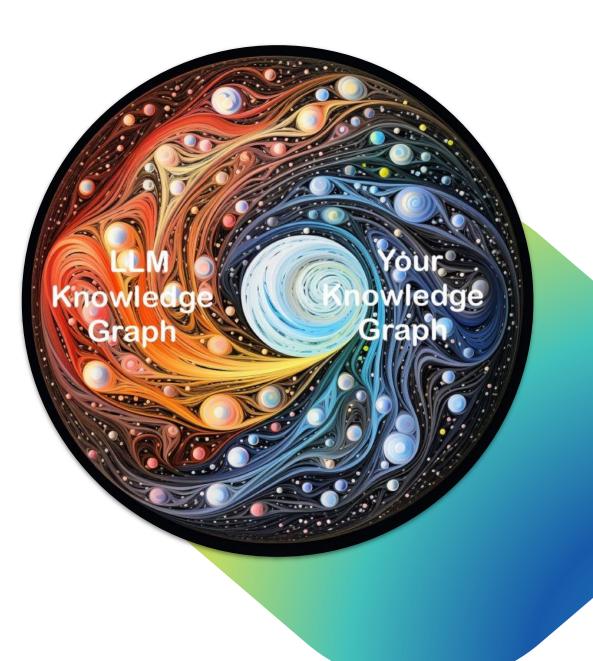
Implementing Knowledge Graphs and developing opinionated data models during the pre-processing stage force AI systems builders to create a more structured user experience and journey. This synchronization with the foundational AI model provides several key benefits:

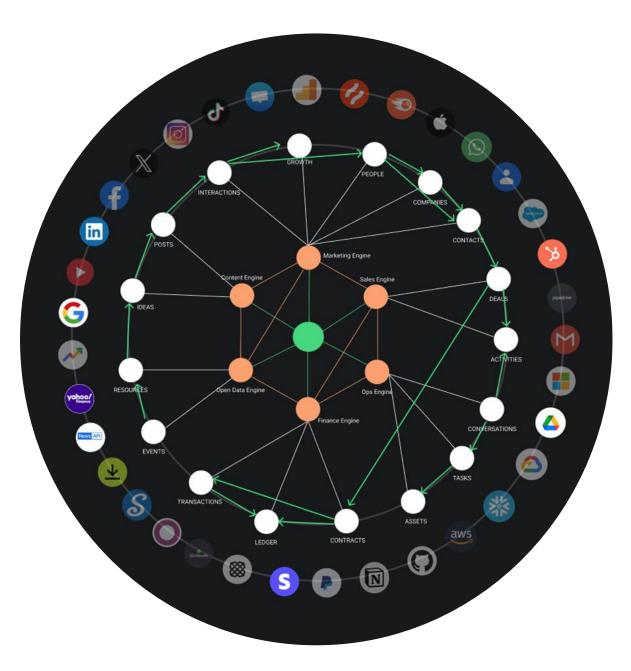
Rich Context: Encapsulates relationships between vast data points, providing deeper insights and more meaningful interactions.

Dynamic Learning: Adapts and evolves with new information, continuously improving performance and accuracy.

Transparency: Offers clear traceable insights into the AI system response, enhancing trust and accountability.

Interdisciplinary Insights: Bridges gaps between different fields of knowledge, for a more holistic understanding of questions.





THE ABI PROJECT: WHAT WE LEARNED

Building Trust Flywheels Through Semantics and Domain Knowledge

Building ABI, an AI system for businesses, we realized the importance of KG and opinionated data models is not even enough; you need to think in terms of flywheel: interconnected and interoperable elements, a logical flow in the head of the user.

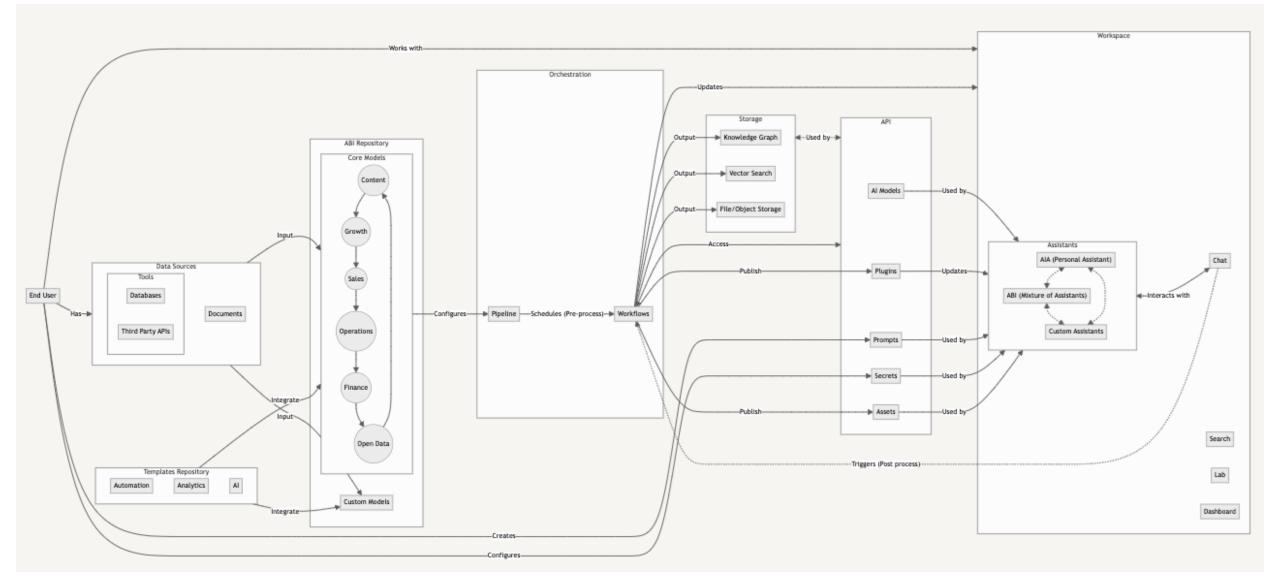
Open Data: External datasets enriches your market understanding, for proactive strategic adaptation.

Content: Standardizing how content is created, tagged, and shared ensures that all communication across channels is consistent and in line with the strategy.

Growth & Sales: Aggregating marketing and sales data create a unified view of qualified contacts and customers interactions and journeys, to build more meaningful relationships.

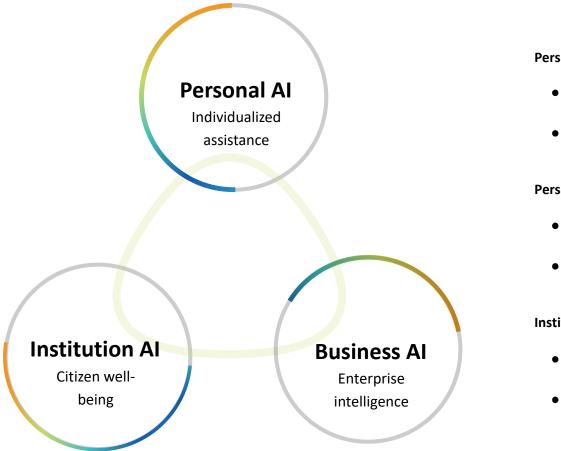
Operations & Finance: Operational tasks to support sales and marketing generates info and assets financial metrics provides a holistic view of business performance.

Our Work Toward a Universal Data & AI Platform Architecture



The Future of Semantic AI

Connecting Personal AI, Business AI, and Institutional AI to enhance personal, business, and societal trusted outcomes.



Personal AI \leftrightarrow Business AI:

- Personal preferences and behaviors (from Personal AI) can inform business strategies (in Business AI) for targeted marketing and personalized customer service.
- Business insights and market trends (from Business AI) can help individuals make informed decisions about products, services, and investments.

Personal AI ↔ Institutional AI:

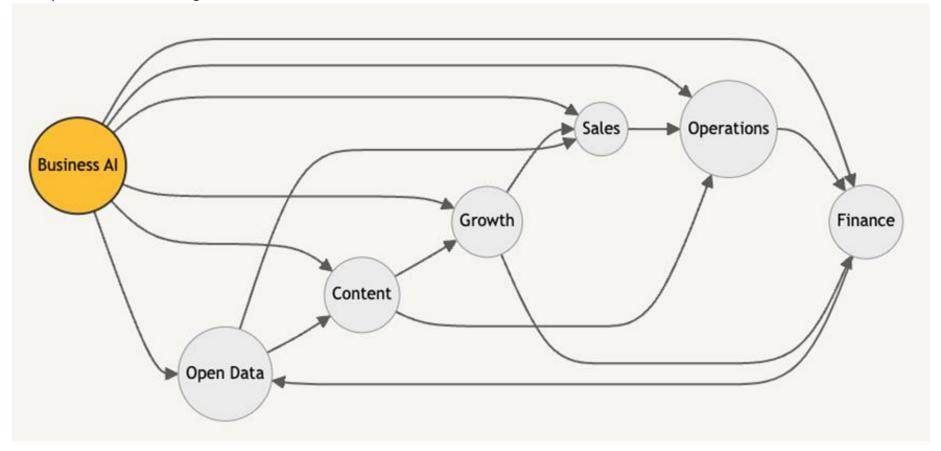
- Educational data and learning progress (from Personal AI) can be shared with institutions to tailor educational programs and resources.
- Institutional research and findings (from Institutional AI) can provide individuals with cuttingedge knowledge and personalized learning opportunities.

Institutional AI ↔ Business AI:

- Academic research and innovation (from Institutional AI) can drive new business opportunities and technological advancements (in Business AI).
- Business trends and operational data (from Business AI) can help institutions align their curricula and research focus with industry needs.

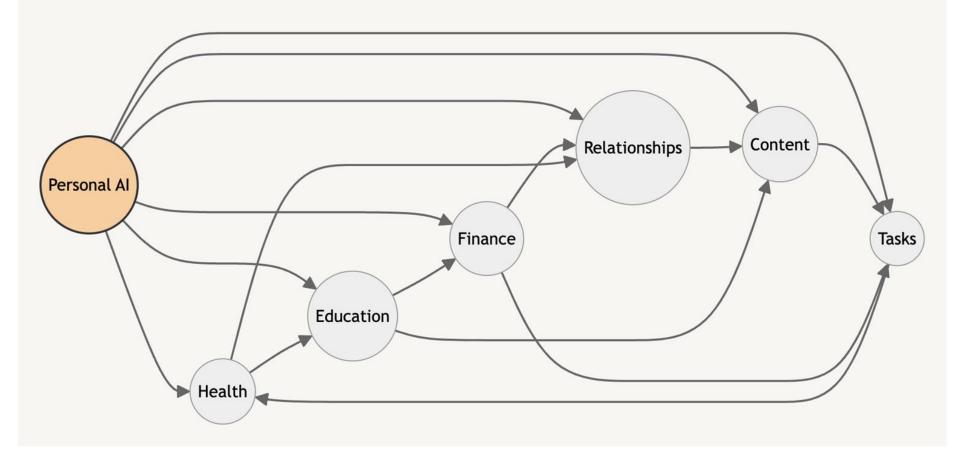
ABI Business AI Flywheel

Open Data enriches market understanding. Standardized Content ensures consistent communication. Growth data unifies audience interactions. Sales data enhances relationship management. Operations support sales and marketing. Finance provides a holistic view for informed decisions. This cycle drives business growth, secures cash flow and drive innovation.



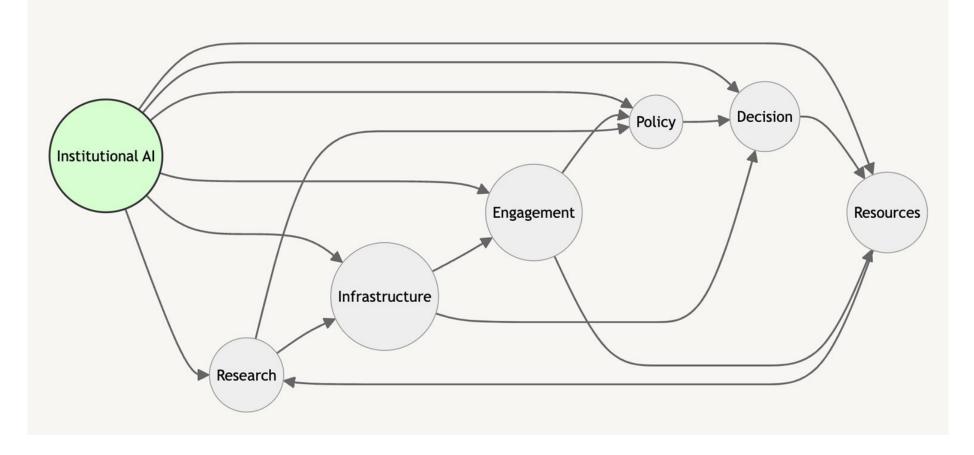
Hypothetical Personal AI Flywheel

In an Personal AI system, Health and Wellness data shapes personalized learning plans. Educational progress influences financial management, leading to financial stability that boosts social interactions. These social interactions refine content recommendations, while productivity tools optimize daily schedules. This interconnected flywheel ensures each aspect of your life enhances the other.



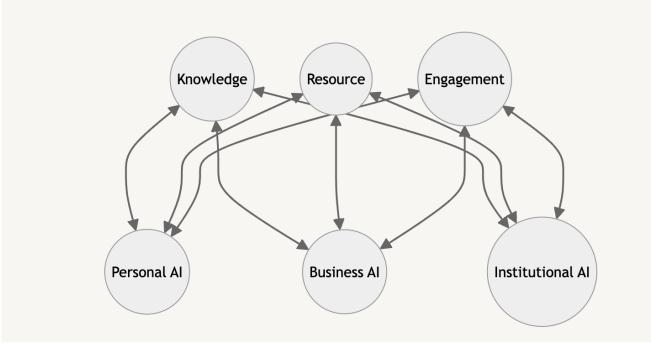
Hypothetical Institutional AI Flywheel

In an Institutional AI system, research and innovation improve the way infrastructure are implemented, boosting engagement by citizens, businesses, and government agencies. Feedback data informs policy updates and ensures compliance with regulations. This compliance data drives decision-making and optimizes resource management, supporting further research and innovation, and enhancing overall institutional performance and citizen well-being.



The Future of Semantic AI: The Case for HyperGraphs

Adopting HyperGraphs, enriched by semantic web technologies (schema.org, LOV, W3C), can create a robust, interconnected ecosystem that drives innovation, efficiency, and personalization, with transparency and accountability.



- Knowledge and Research Engine:
 - **Shared across all three domains** to facilitate the exchange of knowledge, research findings, and innovation.
 - **Examples**: Businesses can fund and collaborate with academic institutions; individuals can access the latest research for personal growth.
- Resource Optimization Engine:
 - Manages and optimizes resources across institutions and businesses, ensuring efficient use of funding, personnel, and facilities.
 - **Examples**: Educational institutions can better allocate resources based on business and personal data insights.
- User Experience and Engagement Engine:
 - Enhances user experience through personalized recommendations and insights based on aggregated data from businesses and institutions.
 - **Examples**: Businesses enhance customer experience; institutions tailor educational programs.

Key Takeaways

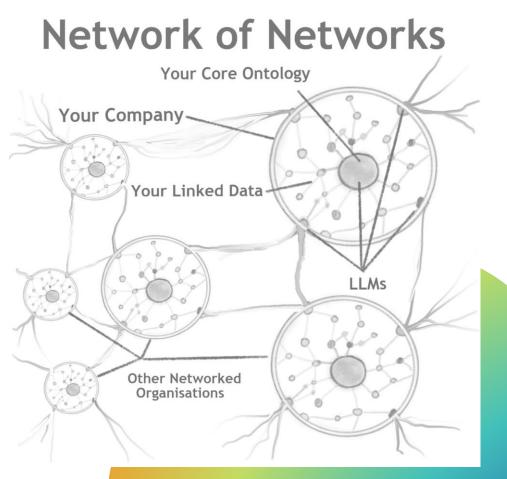
1. Trust in AI is crucial for addressing high-profile errors, bias, privacy concerns, and economic impacts.

2. Semantic interoperability ensures accurate and reliable AI communication by providing a common language and clear data context.

3. Knowledge graphs are essential for providing structure, enhancing transparency, and enabling dynamic learning in AI systems.

4. By structuring our data and building logical bridges between domains, we create unique flywheels that ensure authenticity and independence while creating efficient, interconnected AI ecosystems.

5. The future of AI lies in integrating Personal AI, Business AI, and Institutional AI to drive personalized, business, and societal advancement in a "Network of Networks".

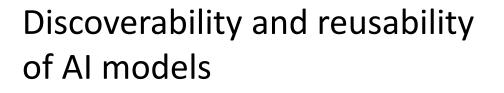


Networks of Networks, by Tony Seal



(d.)



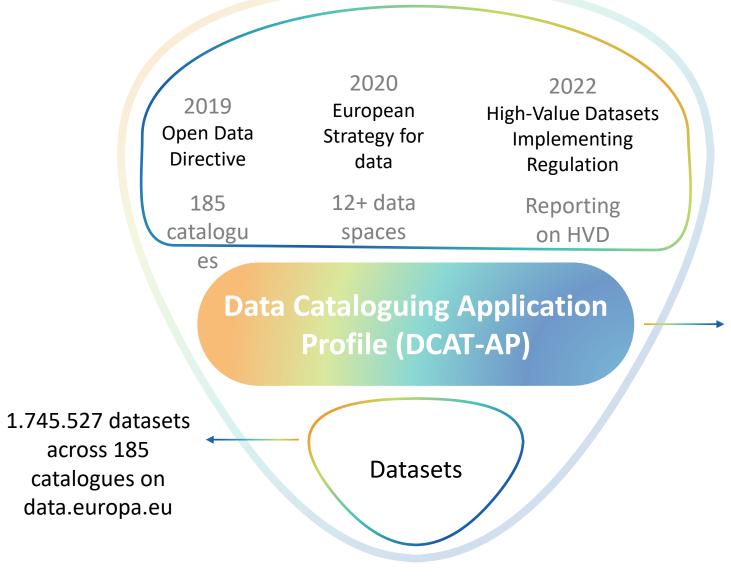


Enhancing the discoverability and reusability of AI models with MLDCAT-AP



The need for MLDCAT-AP

Dataset cataloguing and DCAT-AP

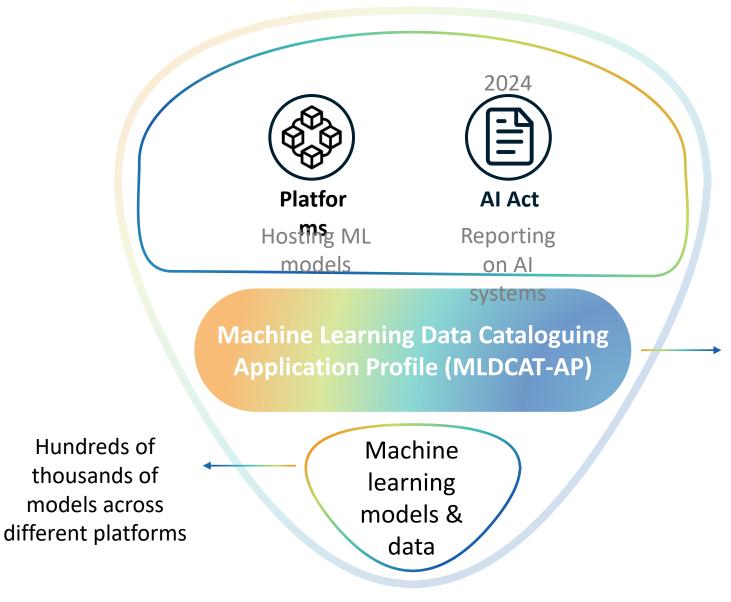


Enabler of cataloguing solutions through:

- standardised description of datasets and catalogues
- effective sharing of datasets and catalogues across portals

Resulting in improved findability and reusability of public sector data across Europe.

MLDCAT-AP in the machine learning environment



MLDCAT-AP harmonises exchange of data across platforms.

MLDCAT-AP standardises description of ML models and datasets, improving:

- findability
- reusability
- reproducibility
- transparency

while incorporating requirements of the AI act.

Challenges ٠ ٠ **Findability** data splits ٠ • ٠ Reproducib • ility User Quality bias • limitations ٠ Risk

Model selection difficult because of:

- Poor description of metadata
- Non-standardised values of metadata

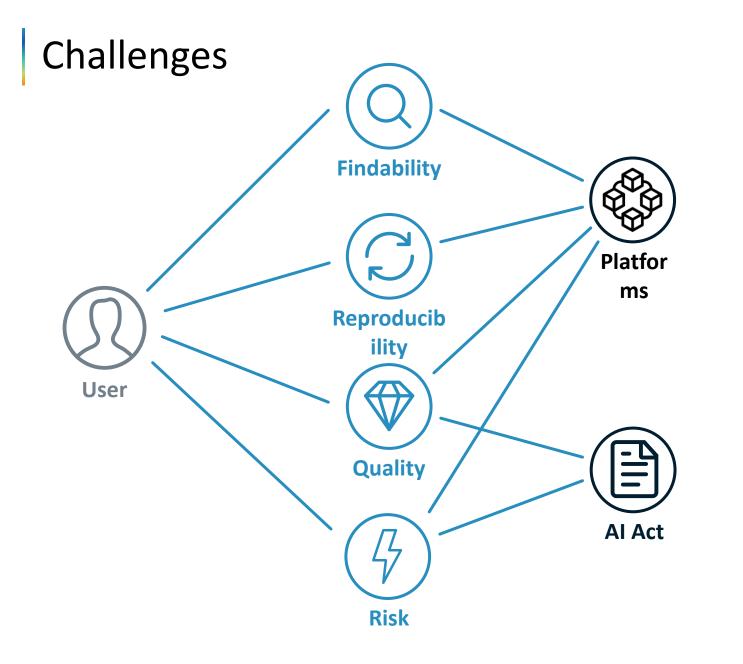
Reproduction of experiments proves hard without proper documentation on:

- preprocessing
- hyperparameters
- license information

Determining the quality of both data used and results of the model. (Cf. AI act)

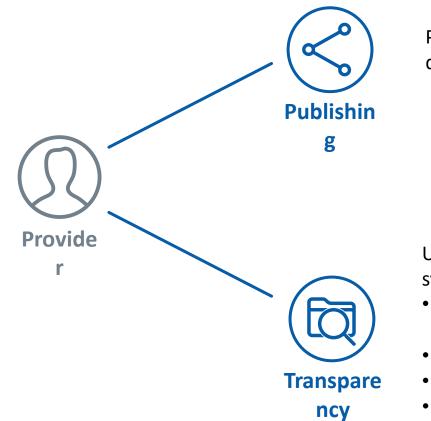
Identifying the risks when reusing a machine learning model can be difficult:







Challenges



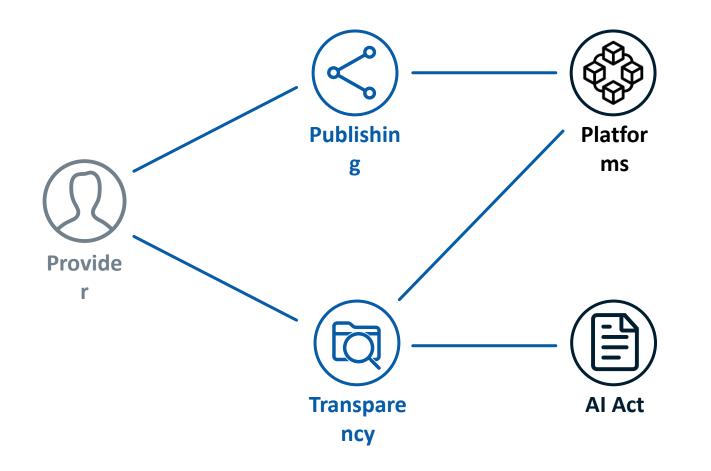
Publication across multiple platforms with different data structures

Under the AI act a provider of a (high risk) AI systems will have to disclose information on:

- the algorithm used for training the machine learning model
- the data used to train the model
- instructions for using the model
- etc.



Challenges

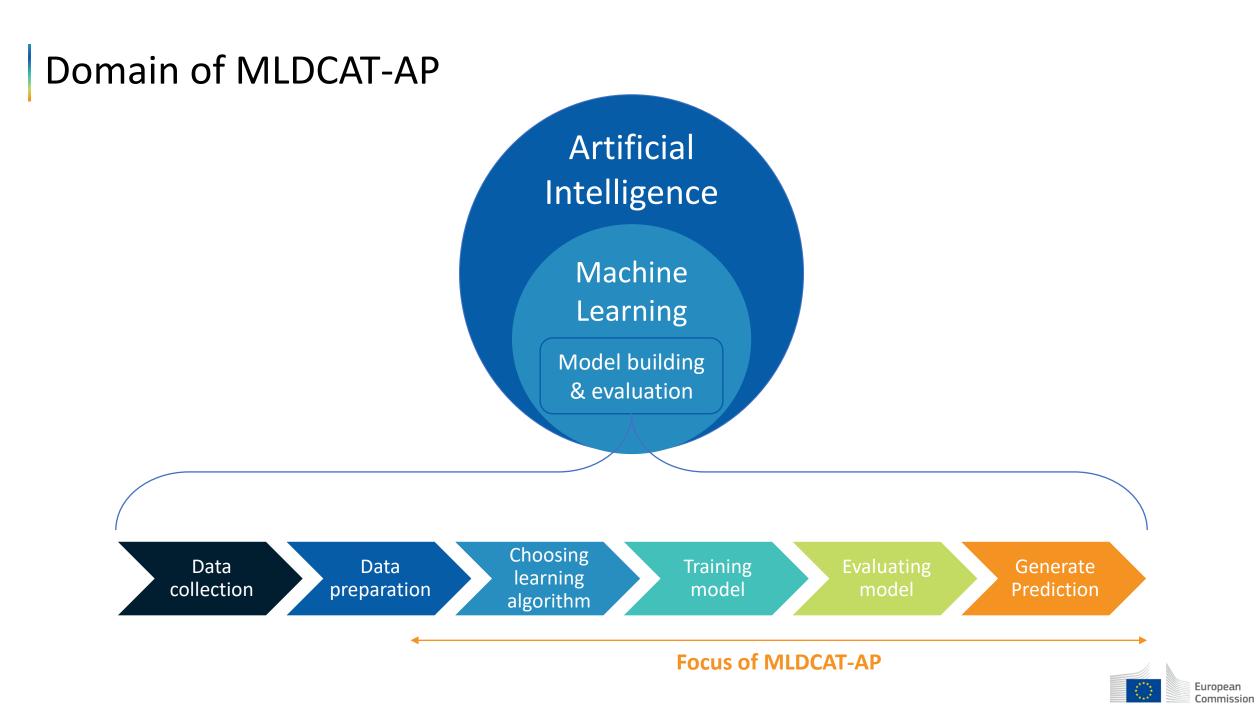




Challenges Findability 60 L Publishin Platfor ms g Reproducib ility Provide User (f)r Quality AI Act Transpare ncy Risk



MLDCAT-AP as a solution



MLDCAT-AP 2.0.0

Concepts reused from **DCAT-AP**

Classes describing the quality of the data

	Choosing learning algorithm	Algorithm class (cf. Al Act)
--	-----------------------------------	------------------------------

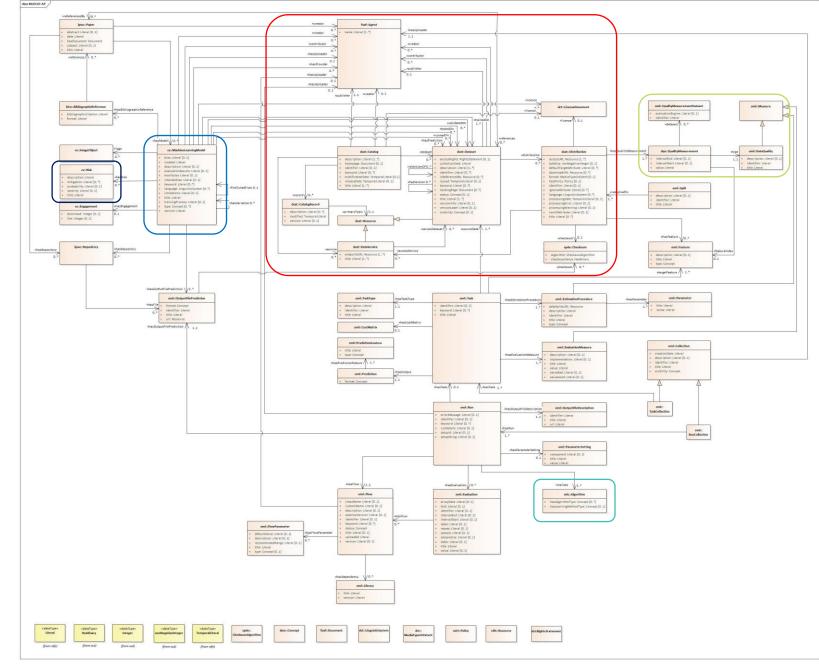
Machine Learning Model class (cf. Al Act)



Data preparation

Risks of the model (cf. AI Act)

Dataset class as output of a Machine Learning Model



MLDCAT-AP – Reusing DCAT-AP concepts



<pre> ElD:31 ⊘verified ■ARFF ■Public ● 2014-04-06 ₽v.1 </pre>		ncy
Jan van Rijn) ♥ 28 likes ▲ 0 issues ▲ 312 downloads		
credit_scoring Economics finance_problem Human Activities mythbusting_1 OpenML-CC18 OpenML100 uci		
Description	t dcat::Dataset	dcat::Distribution
Description Author: Dr. Hans Hofmann Source: UCI - 1994 Please cite: UCI German Credit dataset This dataset classifies people described by a set of attributes as good or bad credit risks. This dataset comes with a cost matrix: Good Bad (predicted) Good 0 Bad 5	<pre>+ accessRights:RightsStatement[0.1] + collectionDate:Literal + description:Literal[1*] + identifier:Literal[0*] + isReferencedBy:Resource[0*] + issued:Literal[01] + keyword:Literal[0*] + landingPage:Document[0*] + status:Concept[01] + title:Literal[1*] + versionInfo:Literal[01] + versionLabel:Literal[01] + visibility:Concept[01]</pre>	+ accessURL: Resource [1*] + byteSize: Literal [01] + checksum: Checksum [01] + defaultTargetAttribute: Literal [01] + downloadURL: Resource [0*] + format: MediaTypeOrExtent [01] + hasPolicy: Policy [01] + identifier: Literal [01] + ignoreAttribute: Literal [0*] + language: LinguisticSystem [0*] + processingDate: Literal [01] + processingError: Literal [01] + processingWarning: Literal [01]
It is worse to class a customer as good when they are bad (5), than it is to class a customer as bad when they are good (1). Attribute description		+ rowIDAttribute: Literal [01] + title: Literal [0*]
Attribute description		

1. Status of existing checking account, in Deutsche Mark.

2. Duration in months

MLDCAT-AP – MachineLea		Quality Transpare Findability
Hugging Face Q. Search models, datasets, users I Models	Datasets ■ Spaces ● Posts ■ Docs ■ Solutions Pricing ~= Log In Sign Up	ney
 bigscience bloomz - 7b1 Vike 133 Text Generation Transformers PyTorch Safetensors bigscience/xP3 46 languages bloom 	Image: state of the state	cv::MachineLearningModel
Model card → Files and versions Ommunity 18	: 🖏 Train - 🕫 Deploy - 🖵 Use this model -	+ bias: Literal [01]
L	Edit model card	+ created: Literal
	Downloads last month 22,421	+ description: Literal [01]
	22,721	+ evaluationResults: Literal [01]
	Safetensors Model size 7.07B params Tensor type FP16 7	+ howToUse: Literal [01]
	Safetensors Model size 7.07B params Tensor type FP16 7	+ intendedUse: Literal [01]
BL***VZ & mT+		+ keyword: Literal [0*]
	🖗 Text Generation	+ language: LinguisticSystem [0*]
	Model is too large to load in Inference API (serverless). To try the model, launch it on <u>Inference</u> <u>Endpoints (dedicated)</u> instead.	+ limitations: Literal [01]
		+ title: Literal
Table of Contents	Datasets used to train bigscience/bloomz-7b1	+ trainingProcess: Literal [01]
1. <u>Model Summary</u>		+ type: Concept [0*]
	■ bigscience/xP3 Updated May 30, 2023 • ± 356 • ♡ 104	+ version: Literal
2. <u>Use</u>		
3. Limitations	■ bigscience/xP3all ■ Viewer • Updated May 30, 2023 • www.sci.acm 20 • ♥ 23	
4. <u>Training</u>		
5. Evaluation		
6. <u>Citation</u>	Spaces using bigscience/bloomz-7b1 34	

MLDCAT-AP – Algorithm

Reproducibility is essential for validation, innovation and research.

Transparency, in addition, is required for regulatory purposes.

oml::ParameterSetting

- + component: Literal [0..1]
- + title: Literal
- + value: Literal

mls::Algorithm

- + hasAlgorithmType: Concept [0..*]
- hasLearningMethodType: Concept [0..1]

Aligning with the existing class of MLSO.

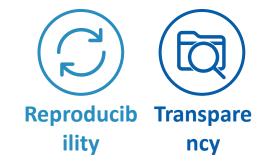
Both properties are populated with controlled lists, examples of values that are mentioned in the AI act are:

Machine Learning Algorithm

- Bayesian
- DeepLearningAlgorithm
- ReinforcementLearningAlgorithm

Learning method

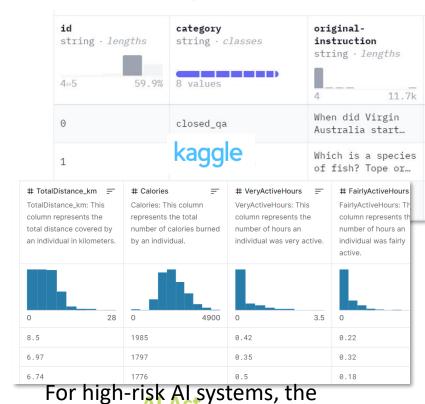
- BayesianLearning
- Reinforcement_Learning_Algorithm



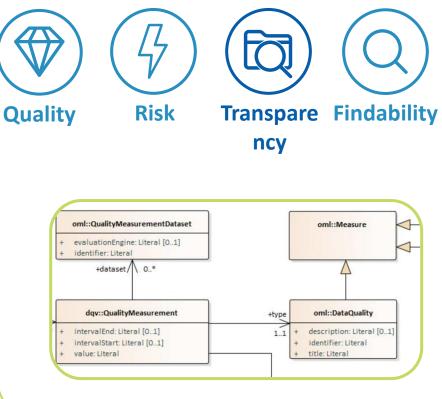
MLDCAT-AP – Quality & Risk

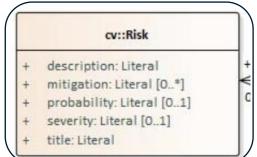
Quality

Hugging Face



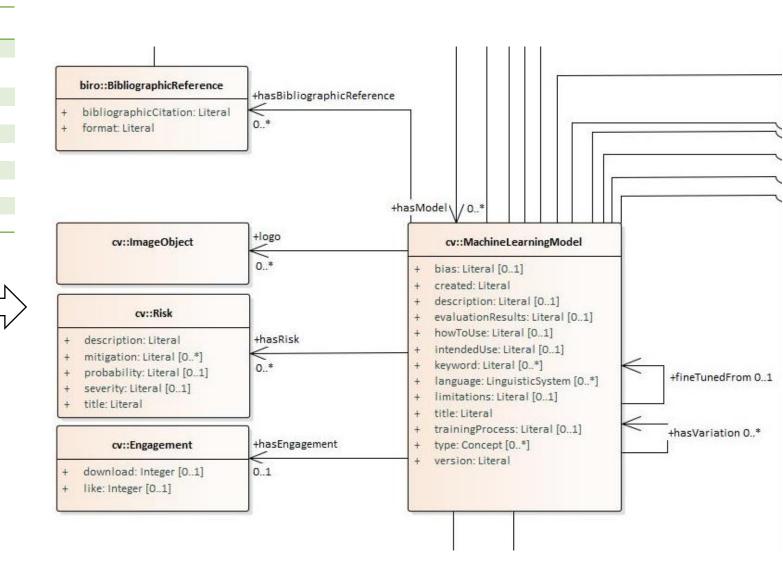
requirements of high quality data, documentation and traceability, transparency, human oversight, accuracy and robustness, are strictly necessary to mitigate the risks to fundamental rights and safety posed by AI and that are not covered by





MLDCAT-AP – Machine Learning Model

Common Properties	Hugging Face 423K models	Kaggle -TensorFlow 278-2K	Pytorch 55	AzureAl 100+ (in org)
Language	Х	Х	Х	х
References to Paper/Code	Х	Х	Х	
How to use	Х	Х	Х	
Logo	Х	Х	х	
Files	Х	Х		х
Likes	Х	Х	X (GitHub stars)	
Downloads	х	Х		
Relation	X (fine tuned from)	X (variation)		
Created date	Х			х
Checksum	Х			Х



Call for action

Call for action

Community building

You are invited to join the MLDCAT-AP community if the topic interest you or can be of use within your organisation by using this link or through helpdesk on the SEMIC Support Centre.

Connecting with platforms

SEMIC is looking for people that can bring us in touch with machine learning platform to facilitate the adoption of MLDCAT-AP, driving interoperability of Machine Learning models and data.



Thank you



inter erable europe

community innovation ∞ govtech ∞

Stay in touch



- (@InteroperableEU) / Twitter
- Interoperable Europe YouTube

Interoperable Europe | LinkedIn

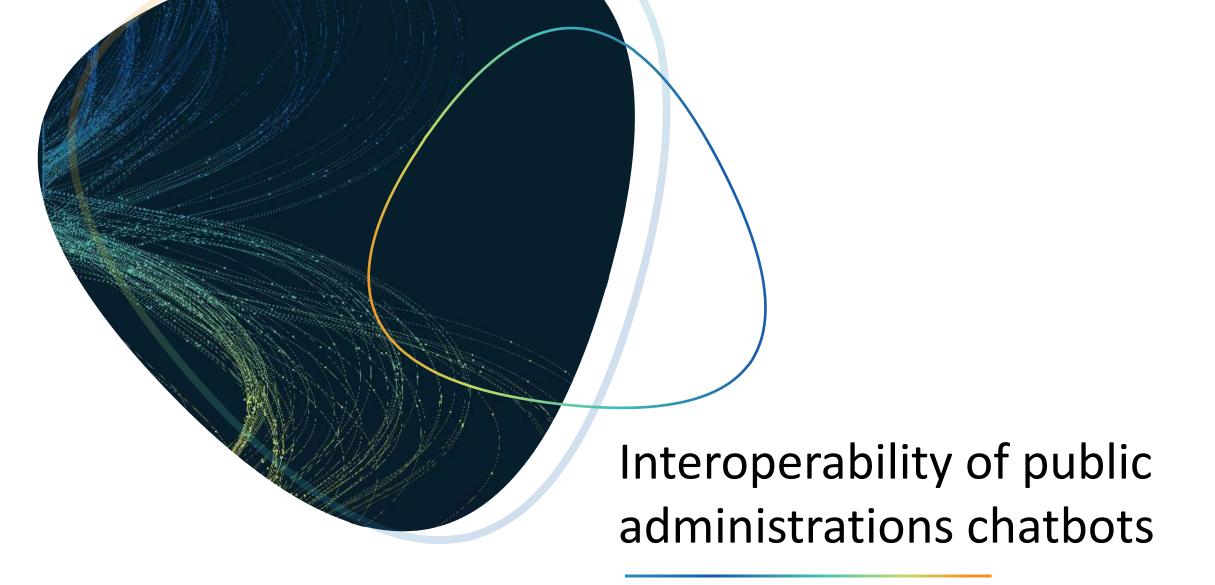


DIGIT-INTEROPERABILITY@ec.europa.eu



Y

https://joinup.ec.europa.eu/collection/interoperableeurope/interoperable-europe



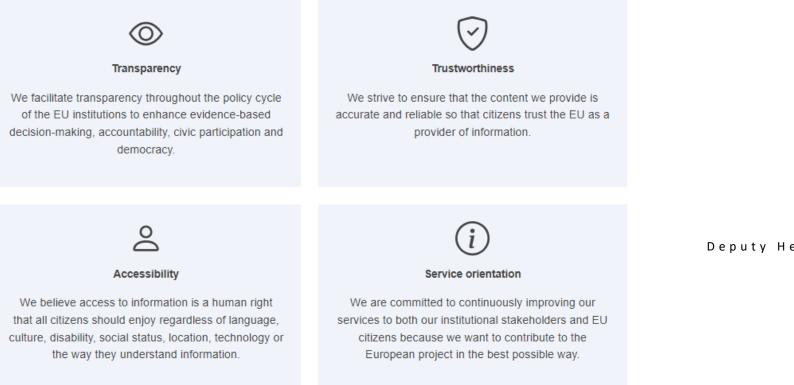
DEP Preliminary study findings – June 2024 Publications Office of the European union



Publications Office of the European Union

Supports EU policies as a center of excellence for information, data and knowledge management

Our values

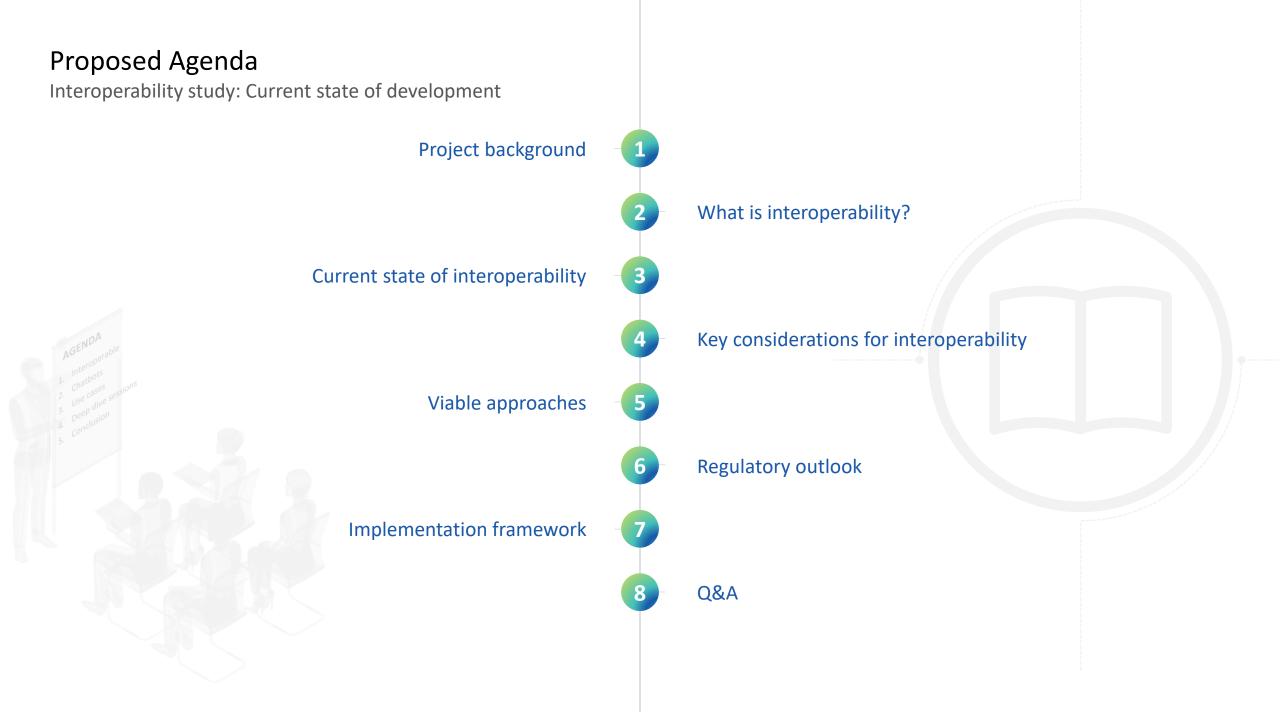


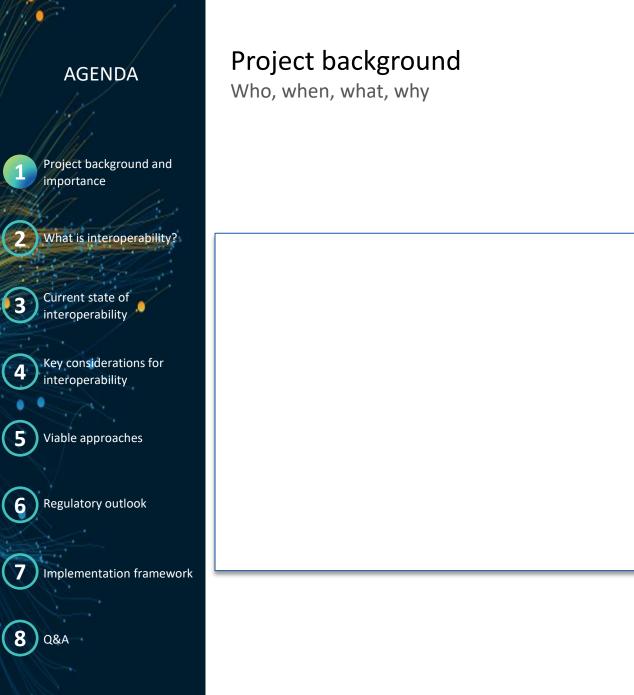


Razvan-Petru Radu

Deputy Head of Unit Portal and Web Services







Why is it important?

%

Establishing interoperability between organizations focussing on both **EU institutions and member states**



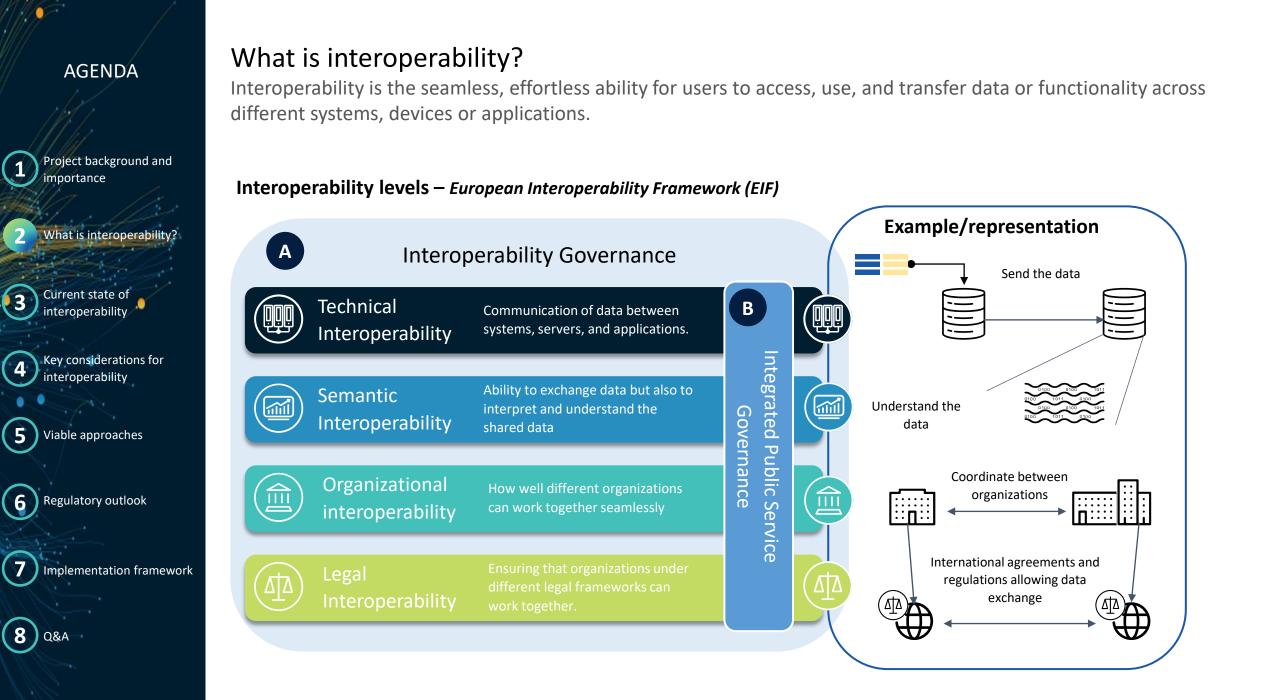
Enhanced multilingual (integrate language from other chatbot) and transparent access to public data and services, looking at latest technologies for virtual assistants

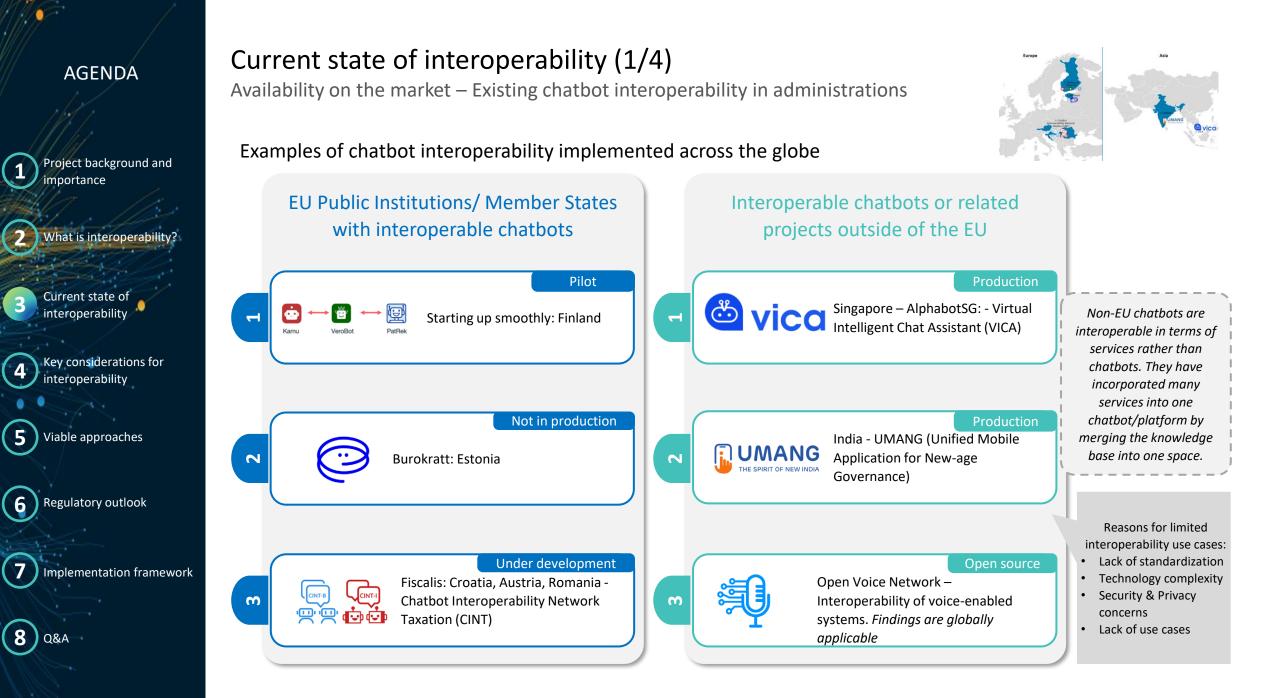


More accessible public administrations

- Seamless, trustable and accurate 24/7 access to public services
- Fully fledged digital services

Readiness to understand and comply with the regulations of the <u>New Interoperable Europe</u> <u>Act</u>, which aims to strengthen cross-border interoperability and cooperation in the public sector across the EU.





Current state of interoperability (2/4)AGENDA Benefits for institutions implementing interoperable chatbots¹ **Benefits** Project background and mportance What is interoperability? Improved service delivery **Better Insights and Analytics** ŧ₽₽ Interoperability facilitates seamless collaboration between Interoperability enables platform providers to gather insights chatbots of public services, improving efficiency and and analytics from multiple chatbot interactions, supporting Current state of accessibility for users data-driven decision-making and platform enhancements interoperability Larger knowledge base **Collaborative network** Key considerations for Interoperable chatbots promote a collaborative network Interoperable chatbots broaden organizations' reach by interoperability pooling information from various sources, offering an among organizations with similar challenges, facilitating shared expansive knowledge base for both employees and customers insights and strategies for collective advancement Viable approaches **Cost-effectiveness** Increased user adoption \sim € Having interoperable chatbots can reduce costs as public Interoperability encourages more businesses and developers to institutions can share technologies and leverage shared adopt the platform, knowing that their chatbots can work egulatory outlook services together with other systems, boosting the platform's user base mplementation framework ¹Non-exhaustive list

Project background and importance

What is interoperability?

Current state of interoperability

Key considerations for interoperability

Viable approaches

Regulatory outlook

Implementation framework

Current state of interoperability (3/4)

Challenges to overcome for institutions implementing interoperable chatbots¹



Infrastructural investment

To establish and maintain interoperability technical resources and infrastructural investment required



Governance models

Complexity in coordinating and governing chatbot interoperability initiatives among different organizations or stakeholders





Compatibility and information asymmetry

Incompatibilities and development challenges in diverse systems can hinder interoperability, potentially causing incorrect responses due to varying platforms, protocols, and data formats

Language barriers

Dialogue translation of chatbots with different languages, especially low-resource languages can limit interoperability



Challenges

Question redirection

A development challenge for interoperable chatbot infrastructure is effectively managing question redirection and corresponding answer display



Conversation flow & handoff

Managing conversation flow, context retentivity, and user experience consistency during cross-bot interactions presents technical and design challenges



Error handling & recovery

Handling errors during cross-bot interactions is challenging due to diverse chatbot error strategies and recovery capabilities



Consent and session management

Obtaining user consent for data sharing across multiple chatbots, while managing session lifecycles for personalized cross-bot interactions, presents a significant challenge

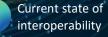
¹Non-exhaustive list

Current state of interoperability (4/4)

Risks to avoid for institutions implementing interoperable chatbots¹

	Project background	and
J	importance	

What is interoperability?



Key considerations for interoperability

Viable approaches

Regulatory outlook

Implementation framework

.

Inadequate interoperability standards Absence of universally accepted interoperability standards and guidelines creates complexity in uniform data handling and communication among chatbots

Performance and scalability issues

Adding additional bots can result in response delays and potential system crashes owing to poor interoperability

Data breaches

Cross-system data exchanges may compromise sensitive data security due to weak integration, leading to potential unauthorized access or malicious activities

Misalignment of responses

Uncoordinated chatbots can produce contradictory responses. Lack of context may lead to repetitive or incomplete information, affecting the user experience



Risks

User experience inconsistencies

Poor interoperability may cause inconsistent branding and user experiences across platforms, leading to trust issues and limited chatbot capabilities



Dependence on vendors/ service providers

Chatbot interoperability could increase vendor dependence, limiting the ability to switch vendors without incurring cost or putting network at risk when parties change vendors.

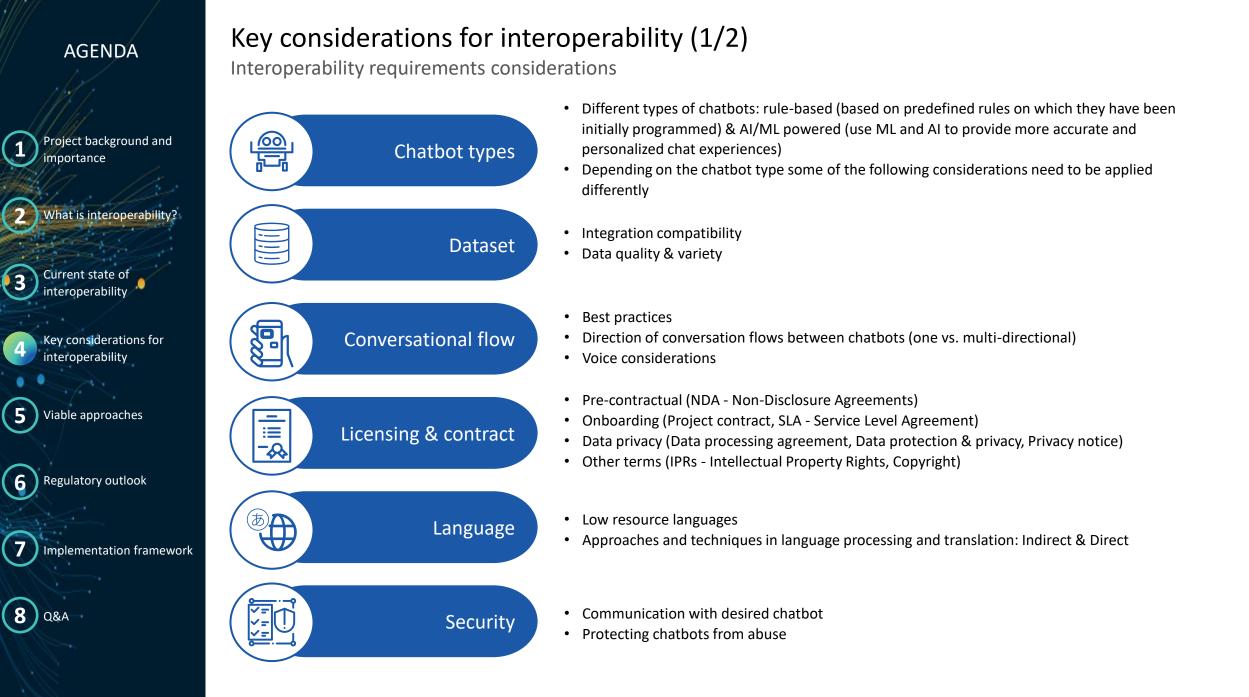


Dependency on other bots in network

A failure, disruption or discontinuation in one bot can affect the functionality of interdependent systems, hindering the entire chain

¹Non-exhaustive list

न्द्रि जिन्द्री



Project background and

What is interoperability

Key considerations for interoperability

Viable approaches

Regulatory outlook

Implementation framework

Current state of interoperability

importance

1

5

6

Key considerations for interoperability (2/2)

Impact of UX/UI principles on interoperability

Important terminology

Host bot: Initial bot interface replying to user (Chatbot A) Contributing bot: Bot transferring content to host bot (Chatbot B)

1. Conversational flow elements - redirections

Option 1: Host bot provides answ contributing bot	wer from	Option 2: Host bot redirects user to contributing bot's interface (a. sharing content, b. Not sharing content)	same interface
Chatbot A	\times	Chatbot A	Chatbot A (Hosting chatbot B) $ imes$
I've asked a friend. This is their answer:		Sorry, I don't have knowledge about this topic. However, my robot colleague chatbot B can help you with this. To ask them click here? Chatbot B	Sorry, I don't know this topic. However, my robot colleague chatbor B can help you with this. Would you like to switch to chatbot B? Yes No
Ask me a question	\rightarrow	Ask r Ask r	Hello, I'm chatbot B, how can I help you? Ask me a question

2. Conversational style (Design & interaction features)

Chatbot design	Chatbot personality	User interaction
···· Number of characters in text	(i) Use of emojis	Transfer transparency
Feedback buttons	Restricted words and topics	Expected interaction speed
Media support	Conversational style (e.g., legal vs. casual)	() Response time & latency

Project background and importance

What is interoperability?

Current state of interoperability

Key considerations for interoperability

Viable approaches

Regulatory outlook

Implementation framework

Viable approaches – Interoperability mechanisms (CKD/ IL)

Sharing domains of knowledge: Central Knowledge Directory (CKD) vs. Interoperability layer (IL)

There are two mechanisms to trigger interoperability:

Central Knowledge Directory (CKD)

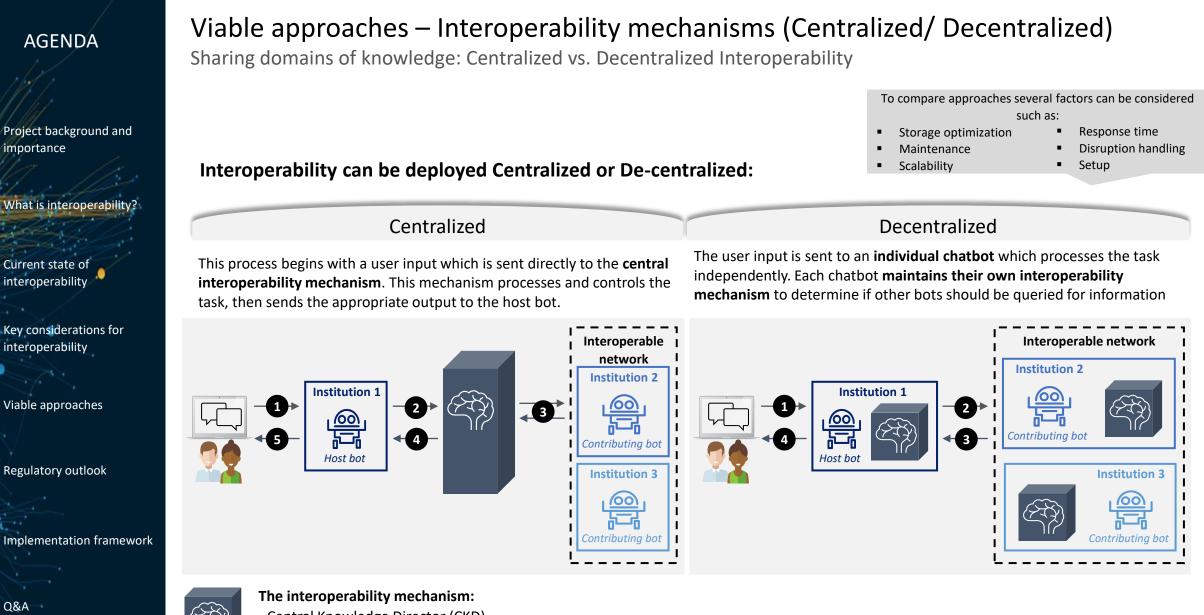
- CKD is a comprehensive catalog of available chatbots, showing their expertise areas and query handling skills. It enables chatbots to understand each other's knowledge domains within the network.
- CKD stores metadata from different chatbots, providing information about their capacity, purpose, and functionality, fostering interaction/transfer between them.

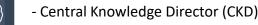
Interoperability layer (IL)

- The Interoperability layer is an intermediate layer between the host bot and the contributor bots.
- Unlike the centralized directory, it **does not store the metadata** of all chatbots, however if knows all bots in the network and can refer to them
- It works through a referral mechanism, taking thresholds of a question's likelihood to be answered by each bot and choosing who to select from the network

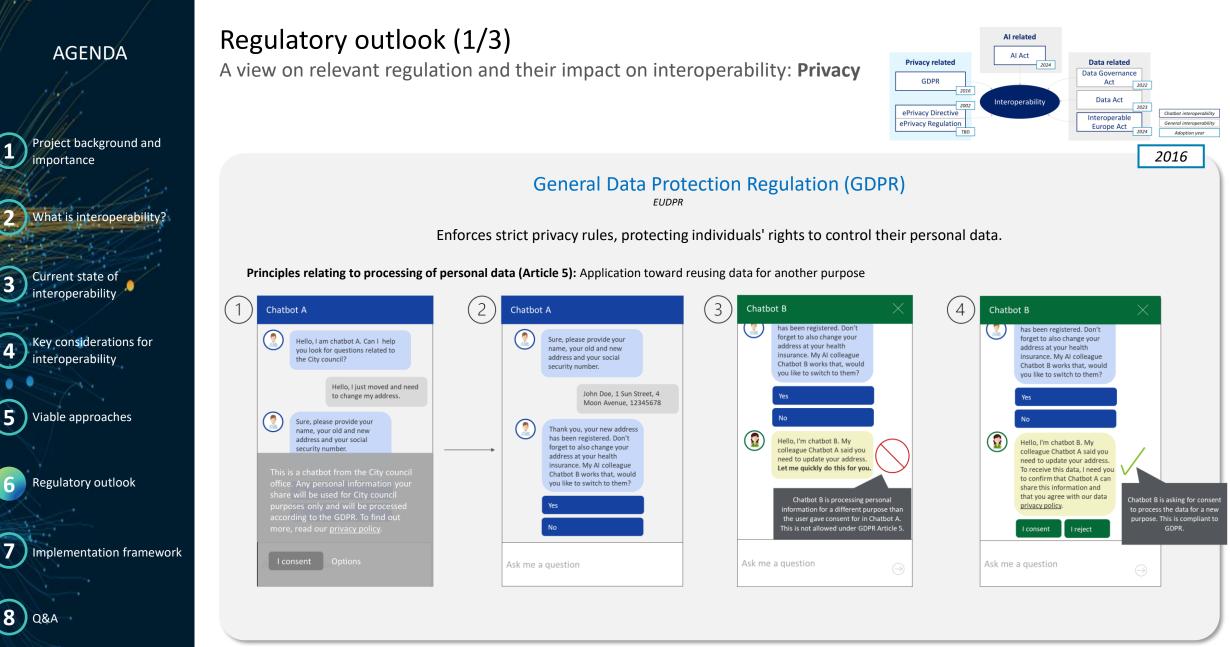
Examples... interoperability transfer mechanisms in action:

Chatbot A which is a tax chatbot is asked on how to file an online complaint for theft. Based on this user input **the CKD** will see which other bot is best to connect to – chatbot B an immigration chatbot or chatbot C a Police chatbot (all this information is stored in the CKD). The CKD transfers the user to chatbot C, the Police chatbot that can deal with topics on theft. Chatbot A (host) forwards the question from the user to chatbot B, C and D **through the IL**. In return, they send the confidence score for this query (indicating how likely each can answer the question). The IL calculates the highest score (if higher than the minimum threshold set) and makes sure that Chatbot A is connected to that bot for getting the related information.

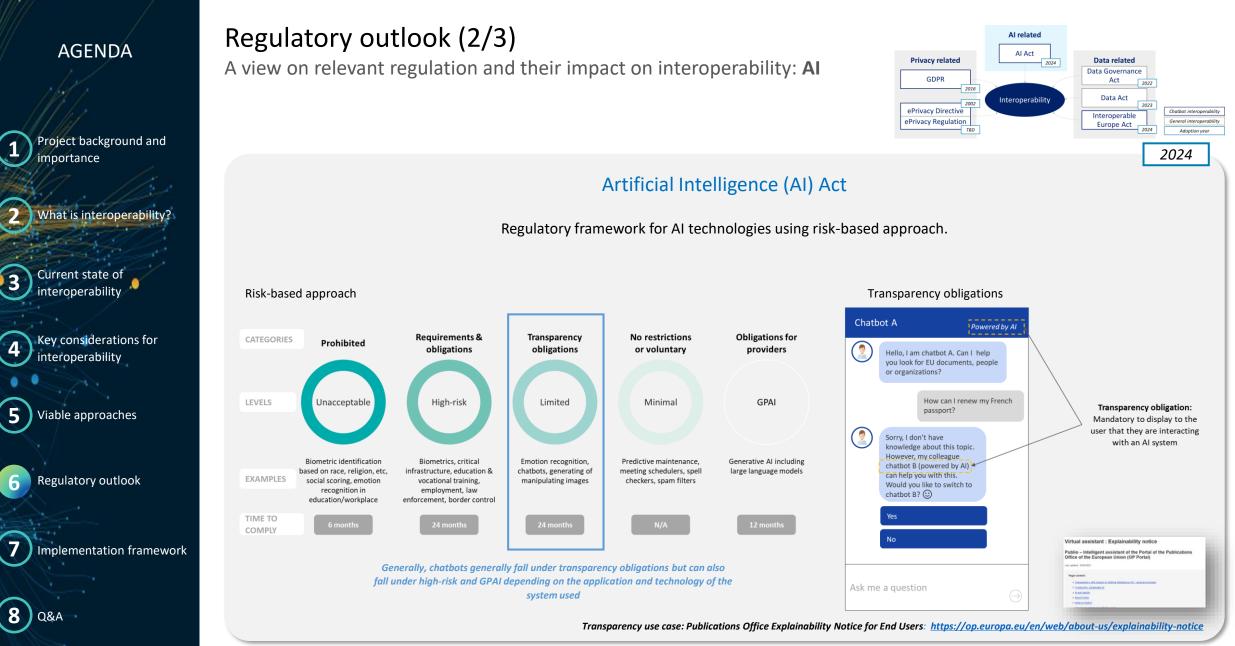




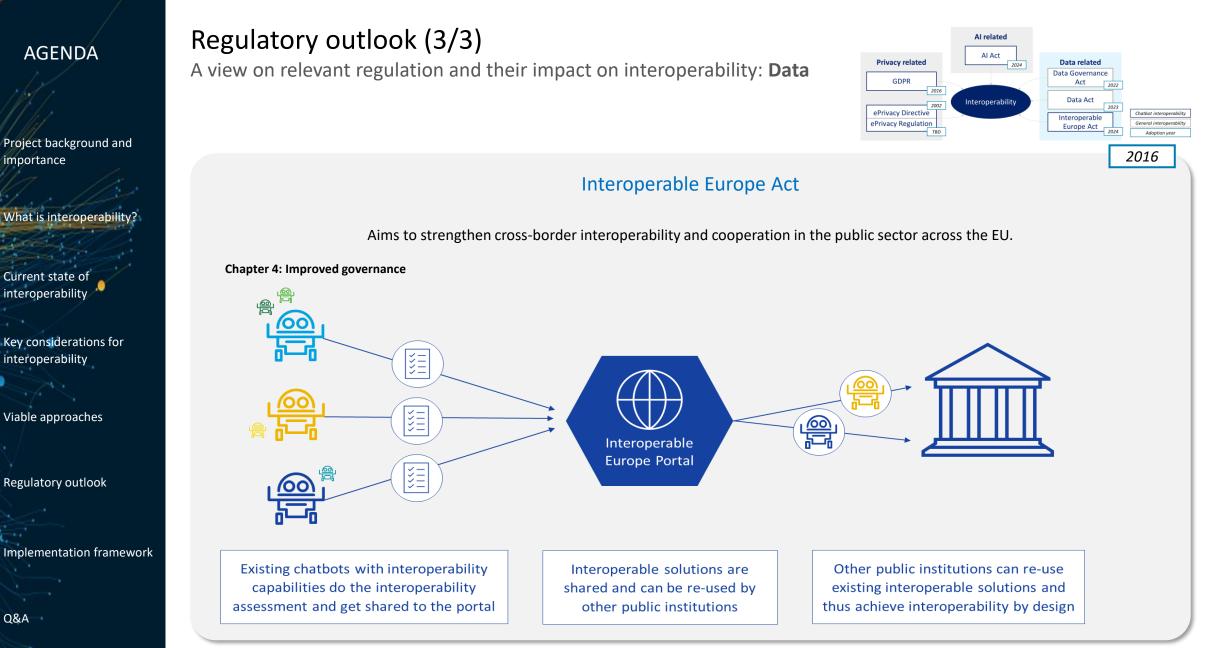
- Interoperability Layer (IL)



DISCLAIMER: Relevance to interoperability shown through selected examples, these present one specific impact, more are or could be applicable for each Act



DISCLAIMER: Relevance to interoperability shown through selected examples, these present one specific impact, more are or could be applicable for each Act



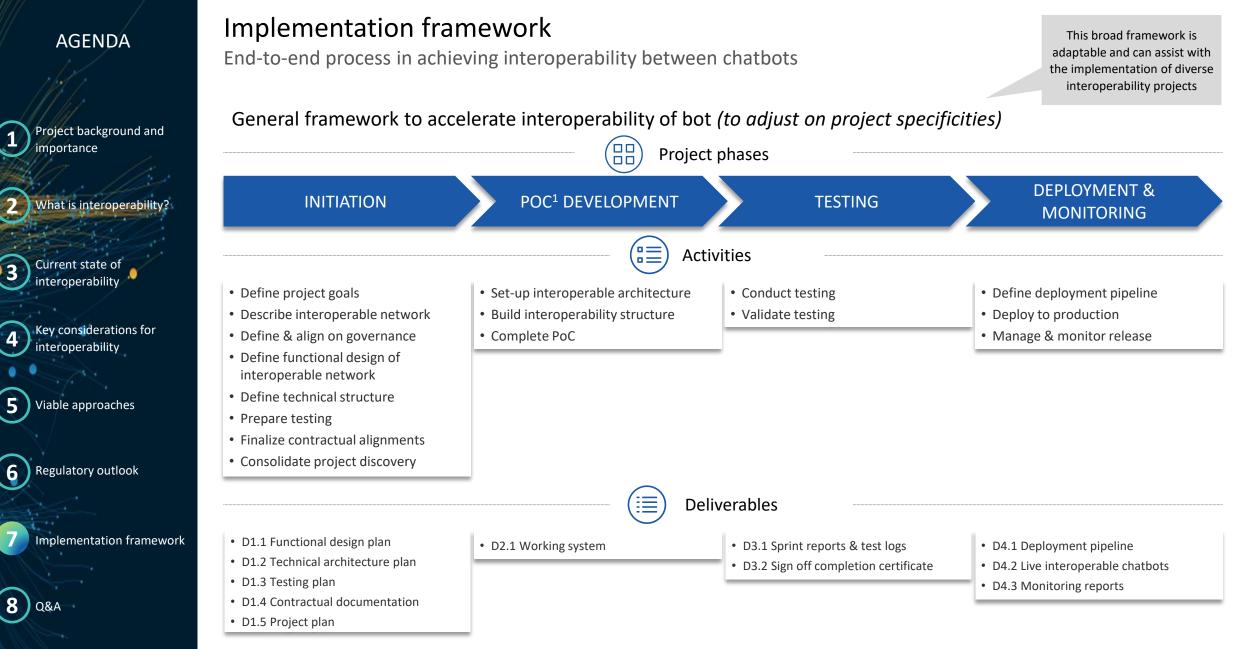
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mportance

DISCLAIMER: Relevance to interoperability shown through selected examples, these present one specific impact, more are or could be applicable for each Act



¹Proof of Concept

Thank you for your attention!

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Any questions?



Panel Discussion

2: Al in support of Interoperability



Join us on Slido!

- Use the QR code
- Or go on slido.com #SEMIC2024Workshops
- Select the correct workshop

We have some questions for you too!



(d.)



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LUNCH BREAK 13:00-14:00 HALL 100

