

aindo

# AI & (Synthetic) Data:

*A New Paradigm in Finance*

# Meet Alessandro di Pietro

Head of Business Development @ Aindo



## Education

- Tor Vergata Biomedical Engineering
- Master II Procurement Management, Tor Vergata Business School
- MBA Digital Transformation, Ticinensis Pavia University

## Expertise & Professional Background

- Expert in AI-driven data innovation for financial institutions
- Specialist in structured synthetic data for highly regulated markets (Finance, Healthcare, Telecoms)
- Secured €10M+ in AI innovation grants & VC funding
- Experience with banks, regulators & fintechs on AI solutions

*AI & Synthetic Data are revolutionizing finance — my goal is to help you understand their role in data accessibility, privacy, and innovation*

## Connect with me



[LinkedIn](#)

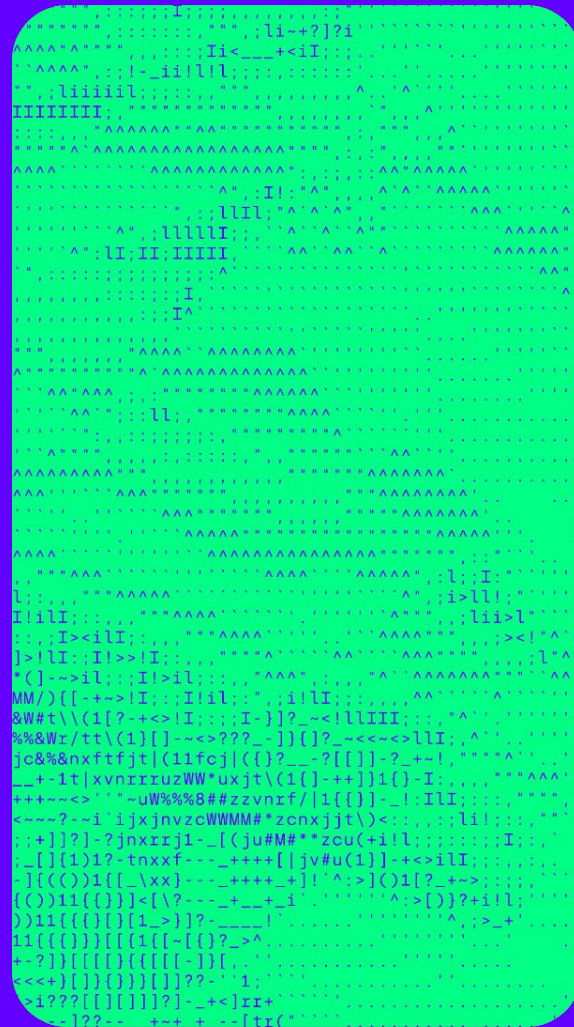


[alessandro@aindo.com](mailto:alessandro@aindo.com)

# Agenda

1. In Aindo Overview: *Building a Deep Tech Startup*
2. The Challenge: *Accessibility and Quality of (Sensitive) Data*
3. Generative AI for Structured Data: *A Multidisciplinary Solution*
4. Synthetic Data: *Application*
5. AI in Finance: *Insurance Focus*
6. Business Models for AI and Data in Europe
7. Interactive Discussion and Use Cases

**Conclusions & Next Steps**







# Aindo Overview: Building a Deep Tech Startup





# Aindo in a nutshell

## Company Info



Aindo SpA (corporation)



Founded in 2018 as a SISSA start-up



2 Co-founders



29 Talents (27% PhD, 65% STEM, 7 nationalities)

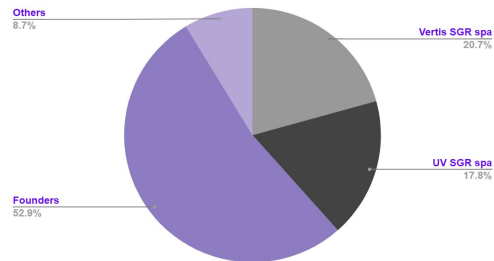


Headquarter in Trieste (TS), Italy

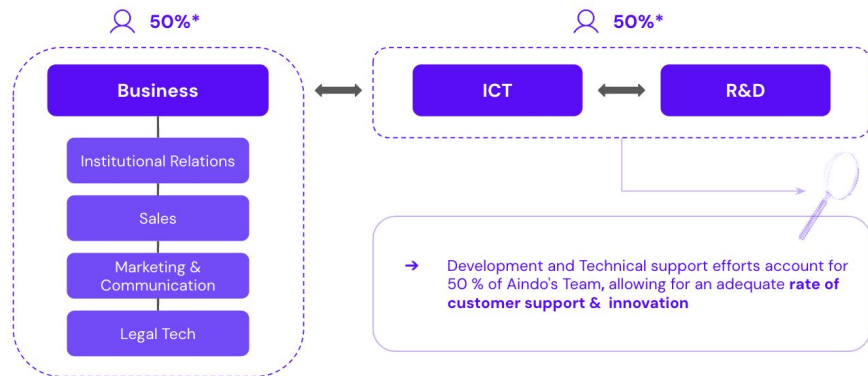


Powered by the support of two leading Venture-Capital (United Venture SGR SpA and Vertis SGR spa) – € 6M series A in Q4 2023

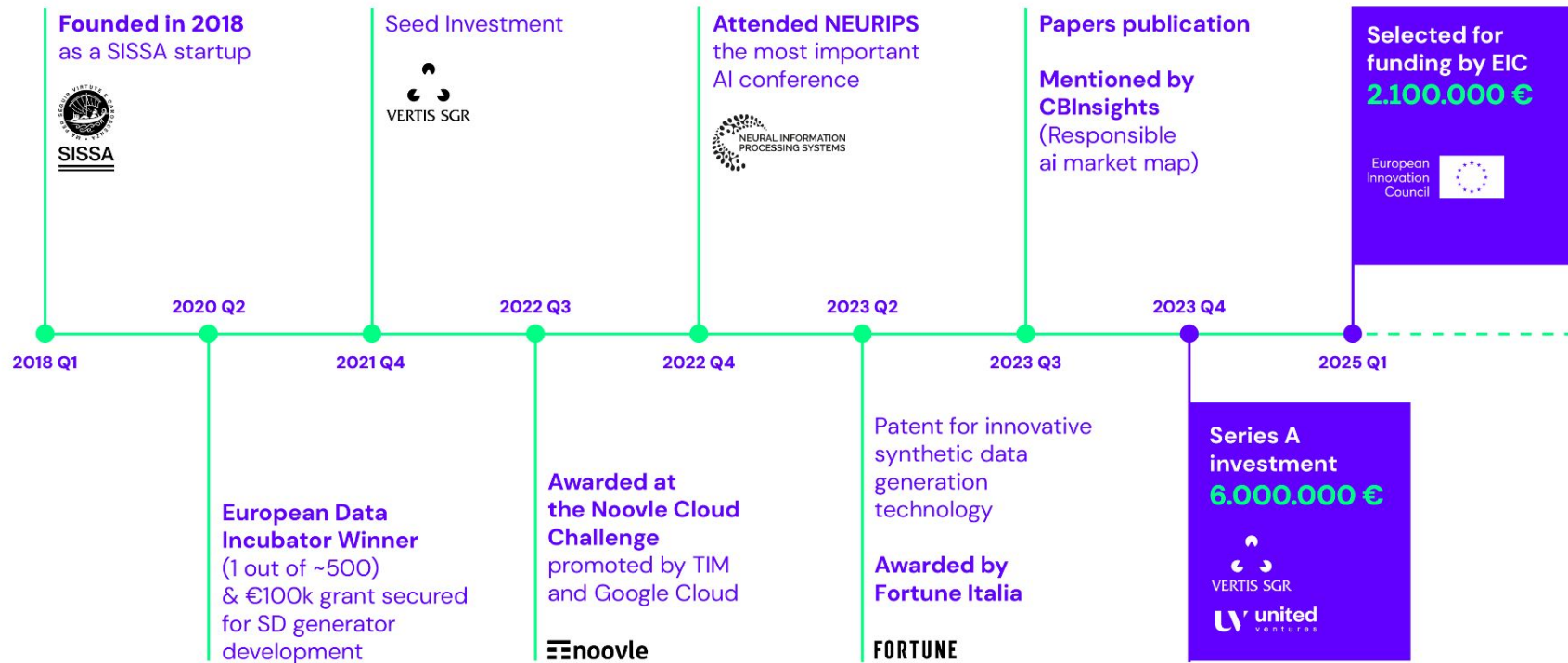
## Shareholders



## Organizational Structure



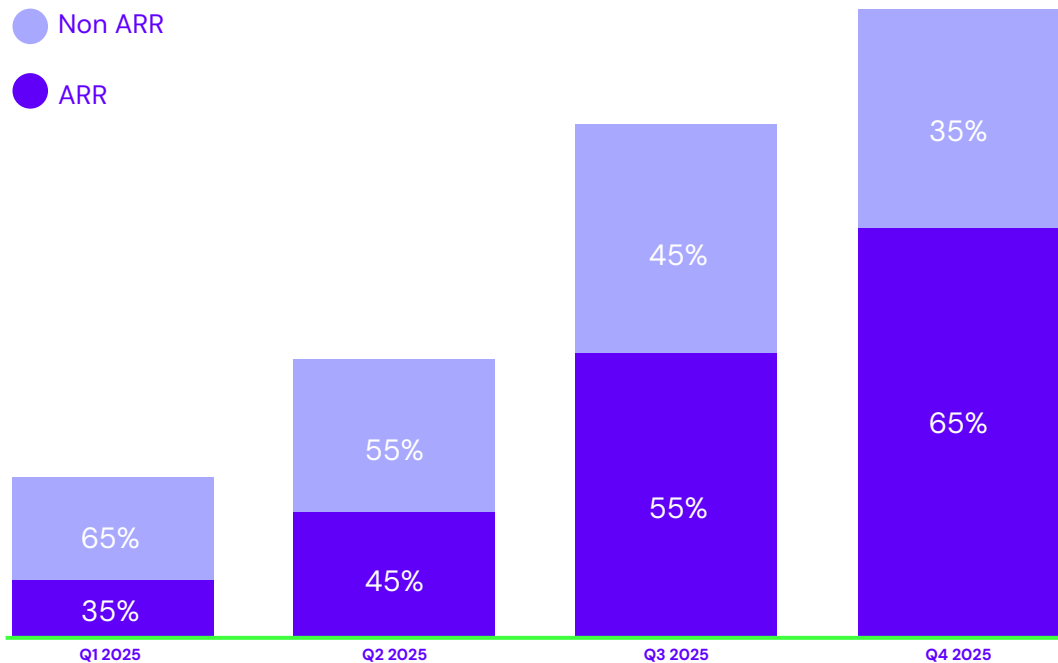
# Growth traction



# Financials & Key Metrics

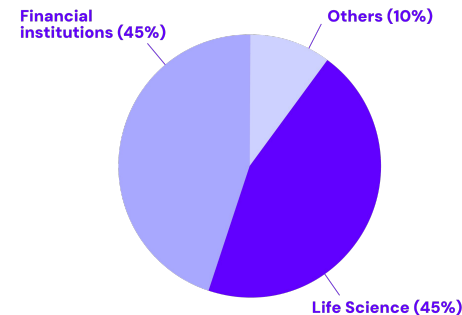
Quarterly revenue target 2025

● Non ARR  
● ARR



Total fiscal year 2024: 2 Million Revenues (o.w. 1 Million ARR)

## Market by industry 2025



## Partners & Customers

**TIM**  
ENTERPRISE

**ARIA**  
AGENZIA REGIONALE PER  
INNOVAZIONE E SVILUPPO

**iFAB**

**AREA**  
SCIENCE PARK

**bip.**

**FANTIX**

**IVASS**  
ISTITUTO ITALIANO  
SULLE ASSICURAZIONI

**Televita**

**Rebel**

**BitBang**

**SISSA**

**National  
Innovation  
Centre  
Ageing**

**MIA CARE**

**insiel**



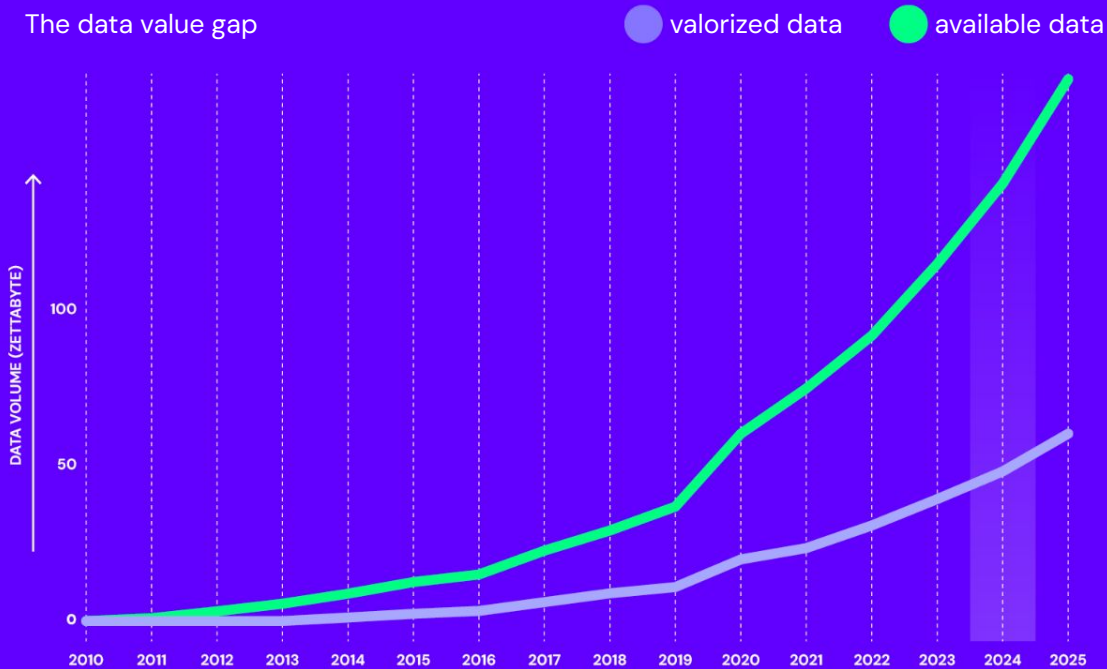
# 2.

## The Challenge: Accessibility and Quality of (Sensitive) Data



# The Challenge

60% to 73% of all potential data value is currently not realized



(Source: Statista; Accenture)

## Core obstacles

- **Data distribution**

Data is stored in different formats and systems, making it difficult to access and integrate.

- **Formatting**

Data is often collected in unstructured, unannotated formats.

- **Privacy**

Privacy legislation (GDPR, CCPA, DP) hinder data exchange and value extraction.

- **Incompleteness**

Data may contain crucial gaps, leading to inaccurate analytics and models

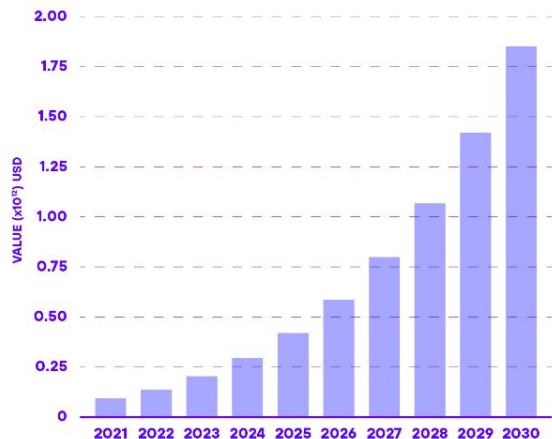
- **Bias and unfairness**

Datasets often underrepresent specific fragments of society, resulting in biased AI models

# AI projected economic & data value by 2030

AI will add 1.5T USD to the global economy by 2030\*

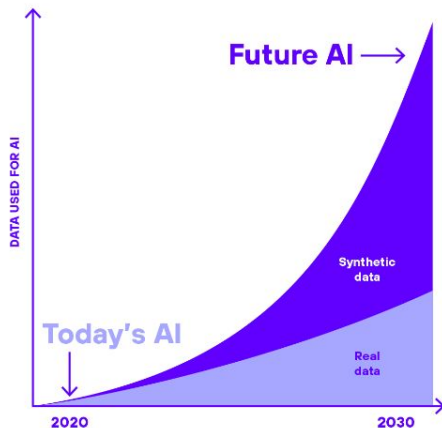
Forecast:  
value of AI sector globally



\*Source: Statista

By 2030, 90% of AI models will be trained on synthetic data\*\*

Forecast:  
use of synthetic data in AI training



\*\*Source: Gartner

## EU Normative landscape



EU Artificial  
Intelligence Act

- Synthetic data should be **preferred over pseudonymized data** or other categories of personal data
- Synthetic data **fall outside the scope of GDPR**, as they are recognized as **non-personal data**
- AI Act 'prefers' use of **synthetic data over so-called 'sensitive' data** when it comes to **correcting biases** in high-risk systems



Data  
Governance  
Act

- Member States should make optimal **use of technologies like synthetic data for privacy protection**















# When is data personal?

General Data Protection Regulation (GDPR) came into effect in 2018

GDPR limits use of personal data

GDPR does not apply to **anonymous data**

**EU 2016/679**  
"Personal data" is one of twelve attribute categories

-  Name
-  Identification number
-  Location data
-  Online identifier
-  Specific physical
-  Physiological
-  Genetic
-  Biometric
-  Mental
-  Economic
-  Cultural
-  Social identity data

# Anonymized: WP29 working definition

WP29 defines  
"anonymized" as not  
susceptible to the  
following three risks



## Singling out

Attacker singles out an individual (in an anonymized) data

## Linkability

Attacker can link an individual's record in the (anonymized) dataset to another record belonging to the same individual

## Linkability

Attacker can deduce the value of a parameter from the data.

## Example Singling out attack

I know that Daniel is a 35-year-old man from Milan, living in Naples.

Can we figure out which record is his Daniel's?

Name	Age	Gender	Town of origin	Residence
Hidden	34	F	Lecce	Parma
	35	M	Milan	Turin
	34	F	Parma	Parma
	35	M	Milan	Naples
	34	F	Palermo	Naples





## Example Singling out attack

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## Example Singling out attack

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Sebastian	35	M	Milan	Turin
Samantha	34	F	Parma	Parma
Daniel	35	M	Milan	Naples
Elsa	35	F	Palermo	Naples



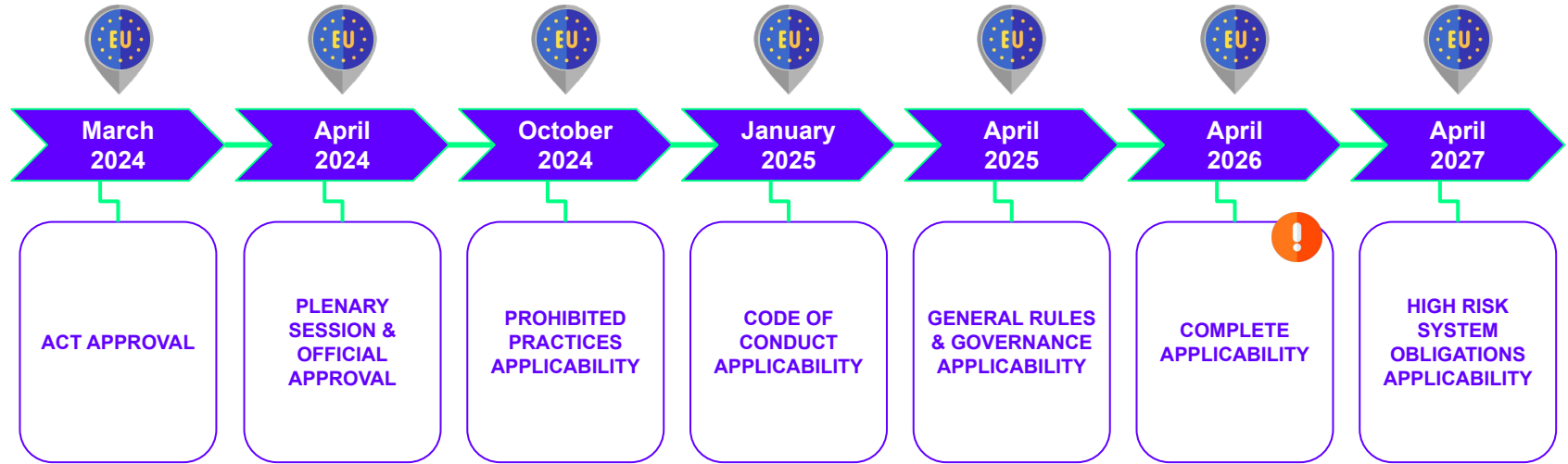
# Example Inference attack

Having singled Daniel out, can we learn any new sensitive information about him?

Name	Age	Gender	Town of origin	Residence	Has disease?
Jenny	34	F	Lecce	Parma	No
Sebastian	35	M	Milan	Turin	No
Samantha	34	F	Parma	Parma	No
Daniel	35	M	Milan	Naples	Yes
Elsa	35	F	Palermo	Naples	No



# AI Act 2024: harmonised rules adoption roadmap



AI Act harmonised rules also apply to already developed systems



# AI Act 2024: a new perspective on Synthetic Data

## Article 10.5

## Article 59

EU legal provisions are interpreted literally in civil law, the legislator equalize anonymous and synthetic data

- De facto considers Anonymized and Synthetic Data equivalent and as interchangeable alternatives
- Set a clear distinction with pseudonymised data: these are listed separately and qualified as a different category

- Equates Synthetic Data with Anonymized and non-personal data, making them falling out of the scope of data protection legislation (GDPR) and falling out of the definition of personal data



Aindo Synthetic data to avoid data compliance breach



## 3.

# Generative AI for Structured Data: A Multidisciplinary Solution

# Synthetic data

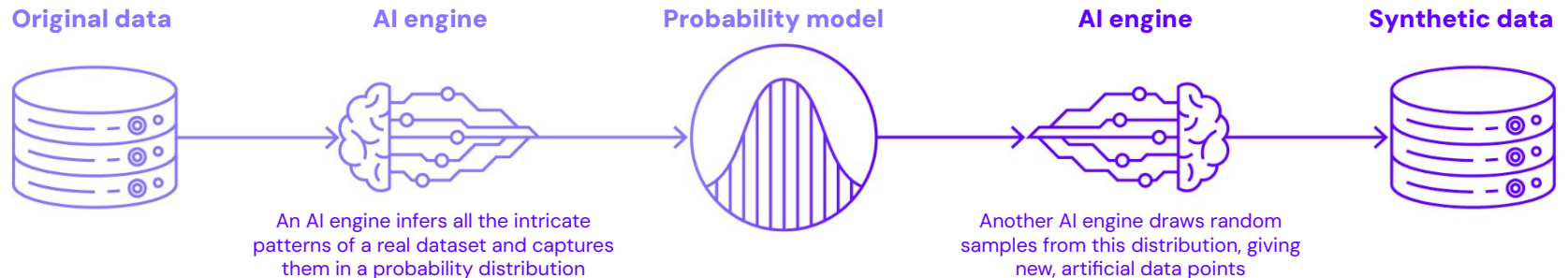
1

Synthetic data are **constructed algorithmically**, they are not collected empirically

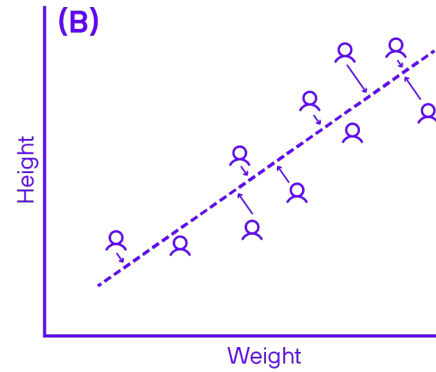
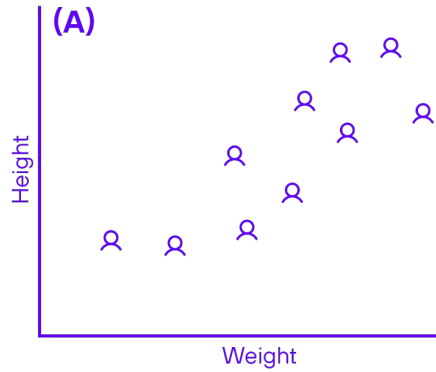
2

Through advances in AI, synthetic data are **indistinguishable from real data**, yet **void of personal information**

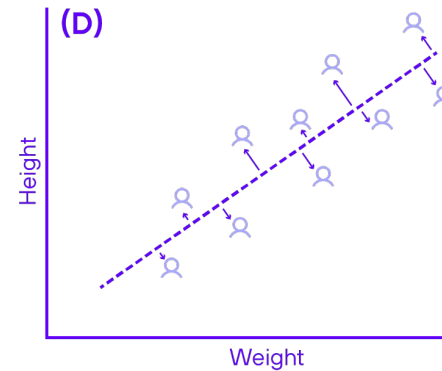
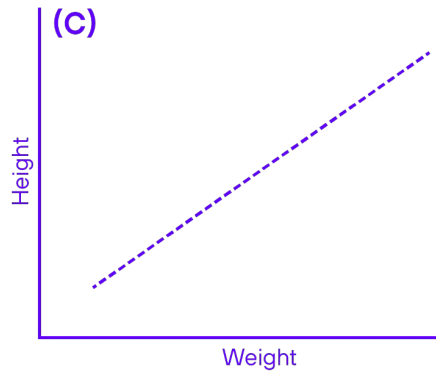
## Under the hood



# Synthetic Data: Replicating real patterns



Real  
Synthetic  
Model



# Generational adversarial networks (GAN)

**Generator**  
criminal

Generates  
counterfeit money



Counterfeit



Real



**Discriminator**  
police

Discriminates between  
real and fake bills



**Pass**  
Light mark



**Fail**  
Dark mark

# Generational adversarial networks (GAN)

**Generator  
criminal**

Generates  
counterfeit money



Counterfeit

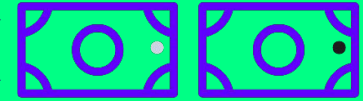


Real



**Discriminator  
police**

Discriminates between  
real and fake bills



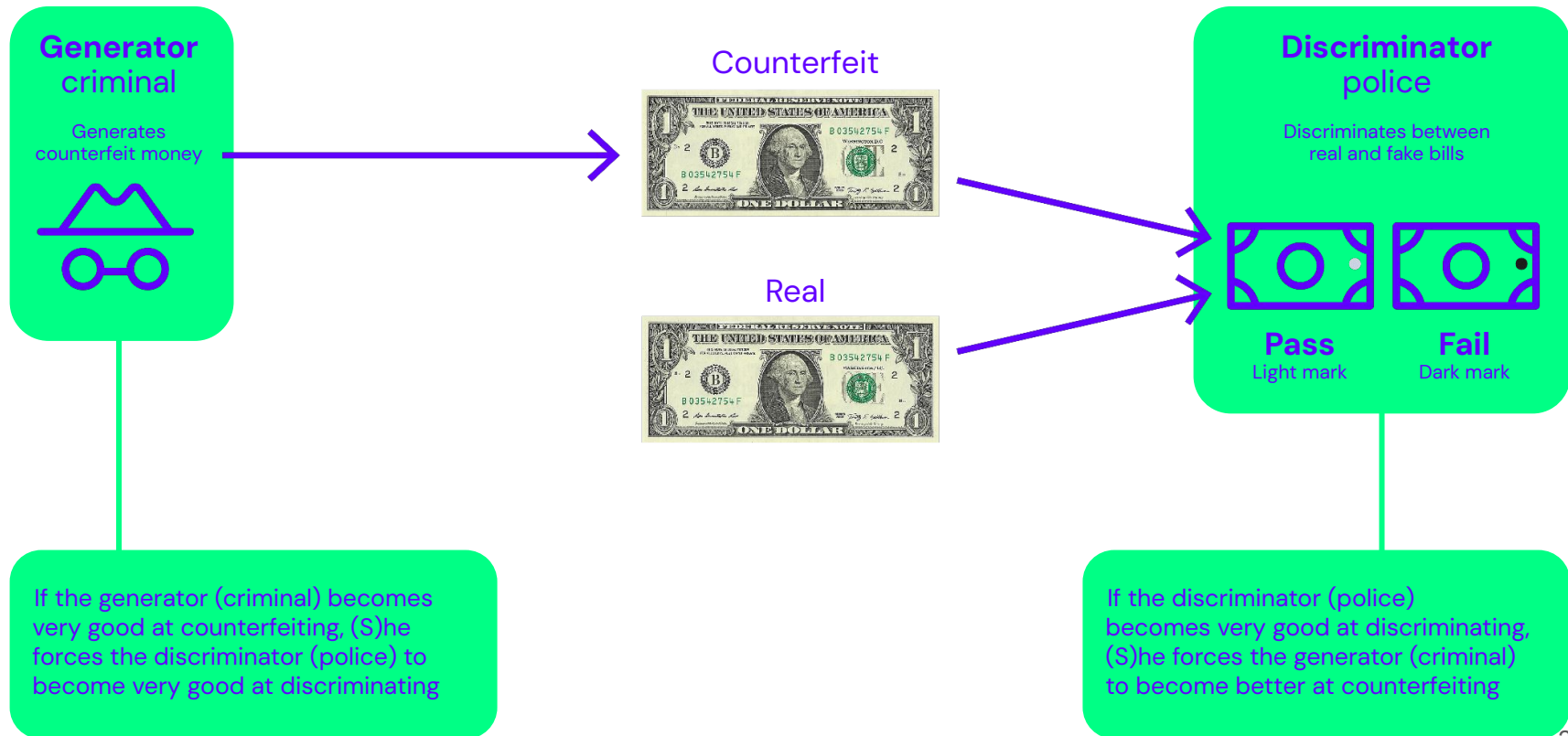
**Pass**  
Light mark

**Fail**  
Dark mark

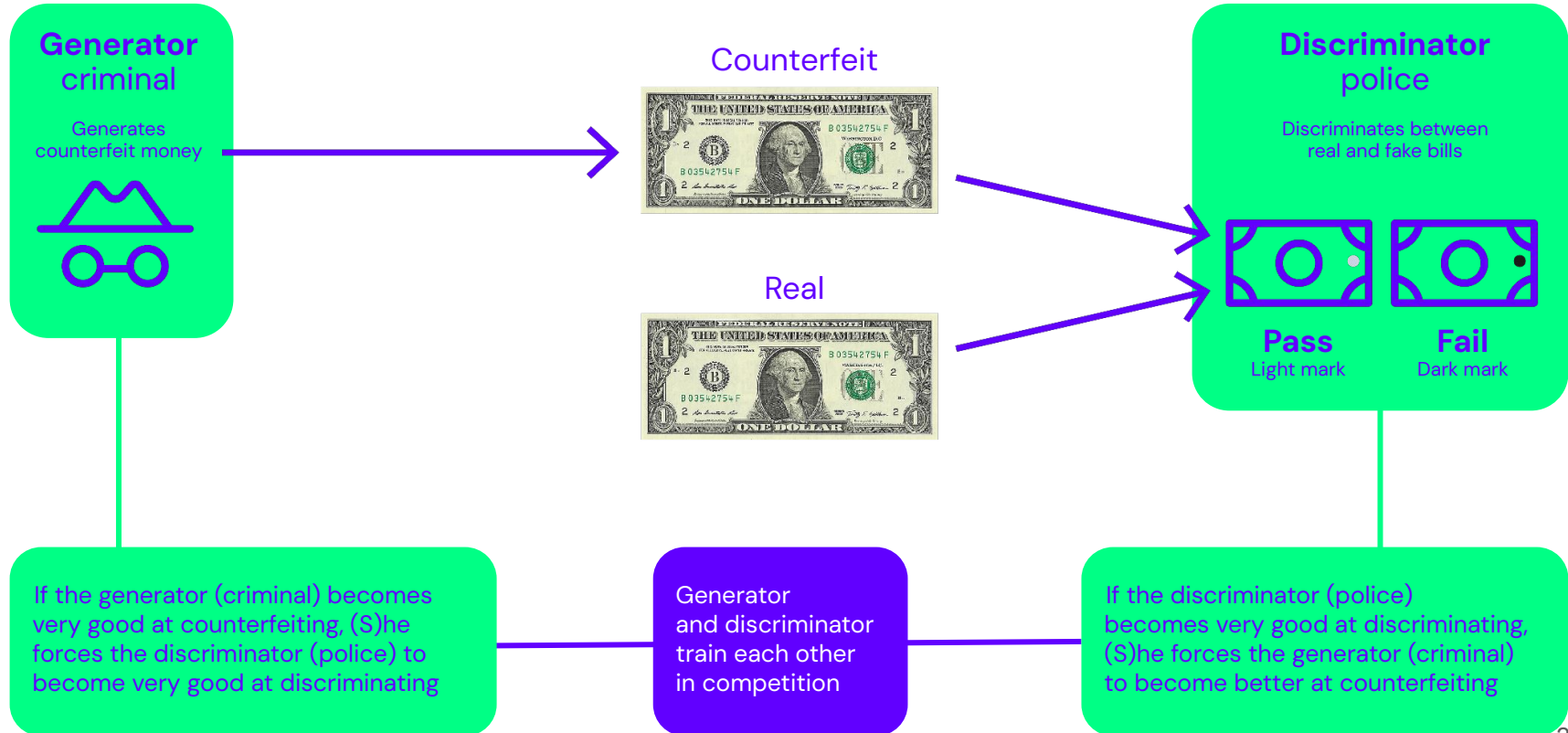
If the discriminator (police) becomes very good at discriminating, (S)he forces the generator (criminal) to become better at counterfeiting



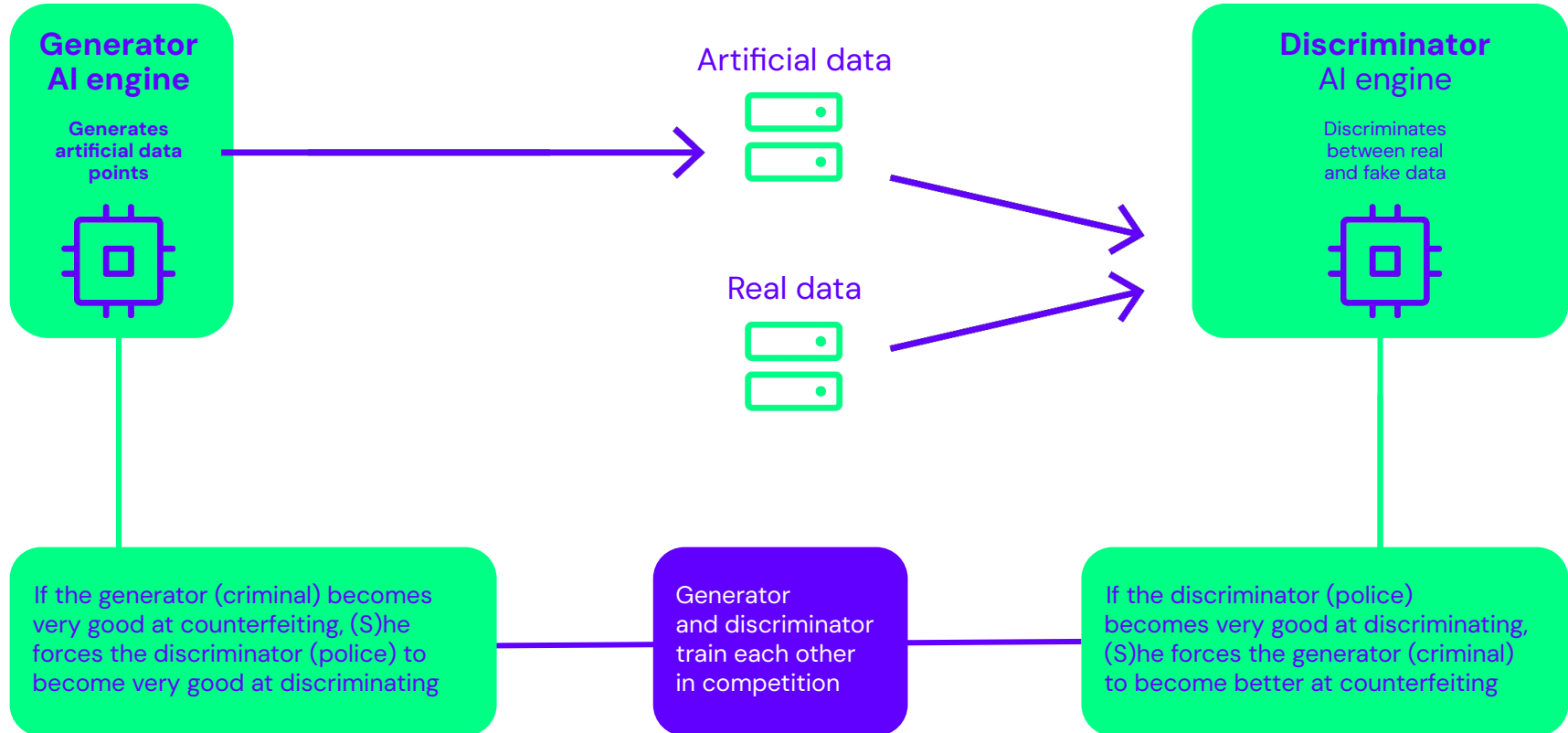
# Generational adversarial networks (GAN)



# Generational adversarial networks (GAN)



# Generational adversarial networks (GAN)



# Hyper-realistic synthetic data that maintains statistical accuracy and preserves privacy

1



Synthetic data are **constructed algorithmically**, they are not collected empirically

## Patented Technology



Ministero delle Imprese  
e del Made in Italy

Our **Gen AI patented technology** represents a key differentiator for our company.

2



Through advances in AI, synthetic data are **indistinguishable from real data**

## Top Tier Technology



Our technology was recognised best-in-class by the **NIST**. Accuracy and privacy outperforms competitors [\(link\)](#).

3



Synthetic data are **void of personal information**. They enhance data **quality** through augmentation by rebalancing and removal of biases.

## Europrivacy certification



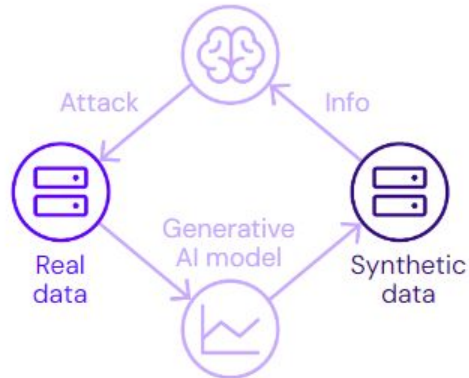
Our technology was certified by **DNV**. Data processing is in compliance with specification requirements v.77 [\(link\)](#).

# Synthetic data: quality assurance



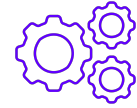
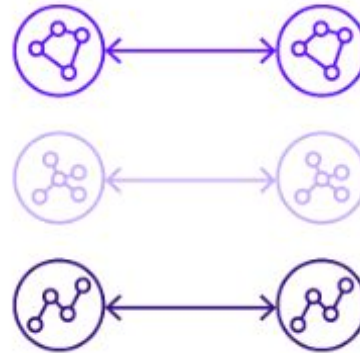
## Privacy

How well does synthetic data use protect the privacy of real data subjects?



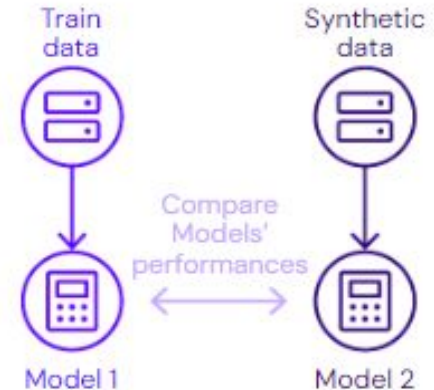
## Fidelity

How well does synthetic data preserve real statistical patterns?



## Utility

How useful are synthetic data in AI training?





# Best performing model, without privacy leak

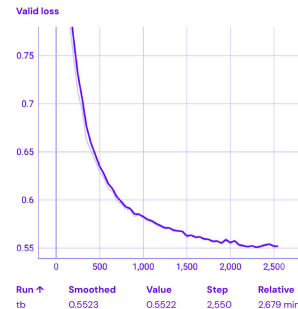
Our technology was recognised best-in-class by the **United States National Institute of Standards and Technology (NIST)** ([link](#)).

The basic privacy mechanism of our synthetic data is **generalization control**: the ability of the synthesizer to learn statistical patterns without learning individual records.

Generalization is controlled through early-stop techniques.

The user can tune the protection level setting a more aggressive early-stop.

Library	Algorithm	Team	$\epsilon$	Utility: SSE	Privacy Leak: UEM
aindo-synth	aindo-synth	Aindo		30.0	0.01
Anonos Data Embassy SDK	Anonos Data Embassy SDK	Anonos		30.0	0.01
Genetic SD	Genetic SD	DataEvolution	10	17.5	0.18
Genetic SD	Genetic SD	DataEvolution	1	5.56	0.04
LostInTheNoise	MWEM+PGM	LostInTheNoise	1	10.0	0.0
MostlyAI SD	MostlyAI SD	MOSTLY AI		30.0	0.01
rsynthpop	catall	rsynthpop-categorical	100	65.0	81.33
rsynthpop	ipf	CRC	10	16.67	14.29
rsynthpop	catall_NonDP	rsynthpop-categorical		50.0	63.37
ydata-sdk	YData Fabric Synthesizer	Ydata		11.85	9.7

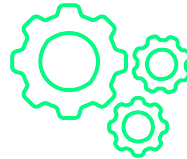
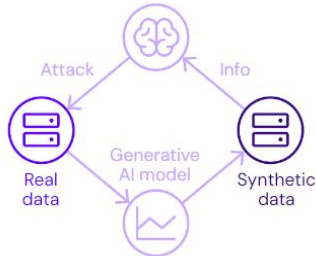


# Data Protection Mechanisms & Metrics



## Privacy

How well does synthetic data use protect the privacy of real data subjects?



## Mechanisms

Synthetisation

### User-controlled privacy mechanism

- Differential Privacy
- Generalisation Control



## Privacy Metrics

**Distance to Closest Record**  
(DCR) metrics

**Deliberate Attacks-Based**  
metrics (Anonymeter)

# 1st Company to be Europrivacy certified



The certification was also issued following the positive outcome of the inspection by the “Guarantor for the Protection of Personal Data (GDPD)” that took place on May 2024

## Supervisor's Inspection Findings

GPDP.Ufficio.PROTOCOLLO.U.0075685.20/06/2024



DIPARTIMENTO SANITA' E RICERCA

AINDO S.P.A.  
Via Pec  
[aindo@pec.it](mailto:aindo@pec.it)

CdS/CL/350777

OGGETTO: accertamento ispettivo sul trattamento di dati personali nell'ambito del processo di produzione di dati sintetici. Esito

In data 30 e 31 maggio 2024 si è svolto un accertamento ispettivo presso codesta Società, al fine di conoscere il processo di generazione di dati sintetici (strutturati e non strutturati) e di verificare tali tipologie di informazioni in relazione ai principi di protezione dei dati personali, con particolare riguardo a quello di minimizzazione. Inoltre, si è inteso verificare l'osservanza delle disposizioni in materia di protezione dei dati personali di cui al Regolamento generale sulla protezione dei dati (UE) 2016/679 (di seguito "Regolamento") con specifico riferimento ai trattamenti svolti per scopi di ricerca scientifica (ordine di servizio del 15 maggio 20224, prot. n. 58759).

L'attività ispettiva è stata verbalizzata e la Società dispone di una copia dei verbali che si intendono integralmente richiamati.

Nella prima giornata di accertamenti, è stato richiesto a codesta Società di illustrare la fase generativa dei dati sintetici a partire dall'addestramento degli algoritmi.

In via preliminare, la Società ha dichiarato che "offre ai propri clienti uno strumento di sintetizzazione che opera sui dataset di cui questi ultimi sono titolari del trattamento e mette a disposizione degli stessi una piattaforma che genera i dati sintetici sulle loro macchine"

## EuroPrivacy Certification Issuance



## DATA PROCESSING CERTIFICATE

Certificate No.  
CB82346

Initial date:  
22 July 2024

Valid:  
22 July 2024 – 21 July 2027

This is to certify that



**AINDO S.p.A.**

Area Science Park - Località Padriciano, 99 - 34149 Trieste (TS) - Italy

is in compliance with relevant requirements specified by the Certification Scheme:

**EUROPRIVACY™/®**

Europrivacy™/® Certification Scheme General Specification Requirements v.77

Target of evaluation is in compliance for the following data processing:

**Generation of synthetic data for the healthcare sector through the design, development, consulting and configuration on customer's premises of a proprietary AI Platform (Aindo Synthetic Data Platform)**



# A comprehensive and flexible offering for fast, secure, and reliable data-mobility

## What We Offer

Aindo specializes in **relational tabular data**. Our solution offers **best-in-class performance**<sup>(1)</sup> and advanced features coupled with a user-friendly interface that makes it **accessible to both experts and non-experts**. This allows seamless integration of synthetic data into data-driven projects, even when dealing with complex data types and formats.

## Core Features

- ❑ **Neural Model Synthesis:** generate complex, relational data and time-series structures using best-in-class models.
- ❑ **Broad Data Support:** handle various formats, including text and geolocation.
- ❑ **Constrained generation:** rebalance your dataset (GUI, SDK) or introduce generation rules (SDK)
- ❑ **Differentially private training:** includes mathematical guarantees of privacy

## Available Through



GUI – Synthetic  
Data **WebApp**



REST **API**



**SDK**

**Comprehensive Documentation**<sup>(2)</sup>:  
detailed guides for configuration and  
usage via GUI, REST API and SDK.

(1) [https://pages.nist.gov/privacy\\_collaborative\\_research\\_cycle/pages/archive.html](https://pages.nist.gov/privacy_collaborative_research_cycle/pages/archive.html)

(2) <https://docs.aindo.com/>

## 4.

# AI in Finance: Insurance Focus



# Data & AI in Insurance

## Market Opportunity of AI Adoption in Insurance

Generative AI market value by 2032

**\$1.3** trillion



AI market in insurance valuation by 2033

**\$79** billion



Gen AI is vital for Risk Detection & New Business Models

**85%** insurances CEOs



### AI POTENTIAL

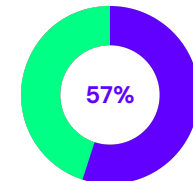
- Claims automation
- Risk assessment
- Personalization
- Combating cybercrime

### SLOW ADOPTION

Adoption among insurers remains slow and siloed, due to **concerns** about the **technology's accuracy**

### CALL FOR AI STRATEGY

- C-Suites** (CTOs, CFOs, CIOs & CEOs) to craft AI strategies
- CAIOs** to rise in Data driven organizations



AI as key technology for achieving business goals in the next 3 years

# Data & AI in Insurance

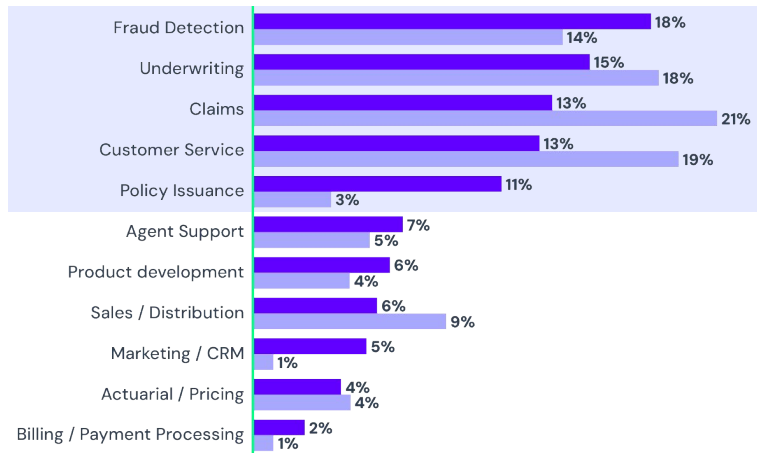
## Use Cases & Benefits

■ 2023

■ 2022

### Breakdown of AI Insurance Use Case by Insurance Process

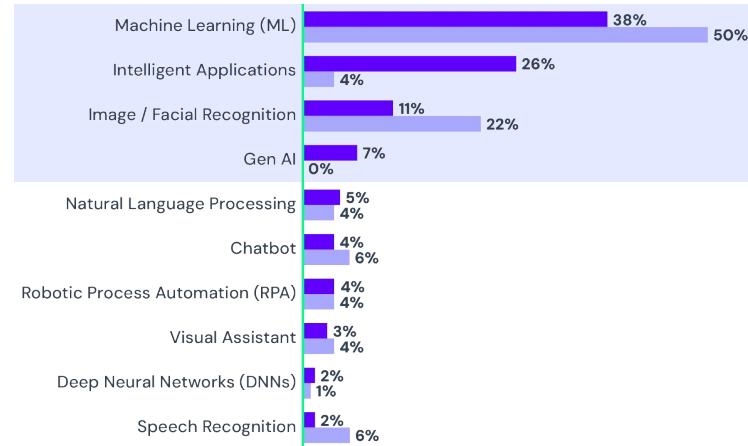
Percentage of cases



n=69 (2022), 76 (2023) use cases in the AI toolkit, analysis by type of insurance process, multiple response allowed  
Source: Gartner Toolkit Artificial Intelligence Use Case for Insurance

### Breakdown of AI Insurance Use Case by Technology

Percentage of cases



n=69 (2022), 76 (2023) use cases in the AI toolkit, analysis by type of insurance process, multiple response allowed  
Source: Gartner Toolkit Artificial Intelligence Use Case for Insurance

Benefits

Cost Efficiency ✓

Accuracy ✓

Scalability ✓

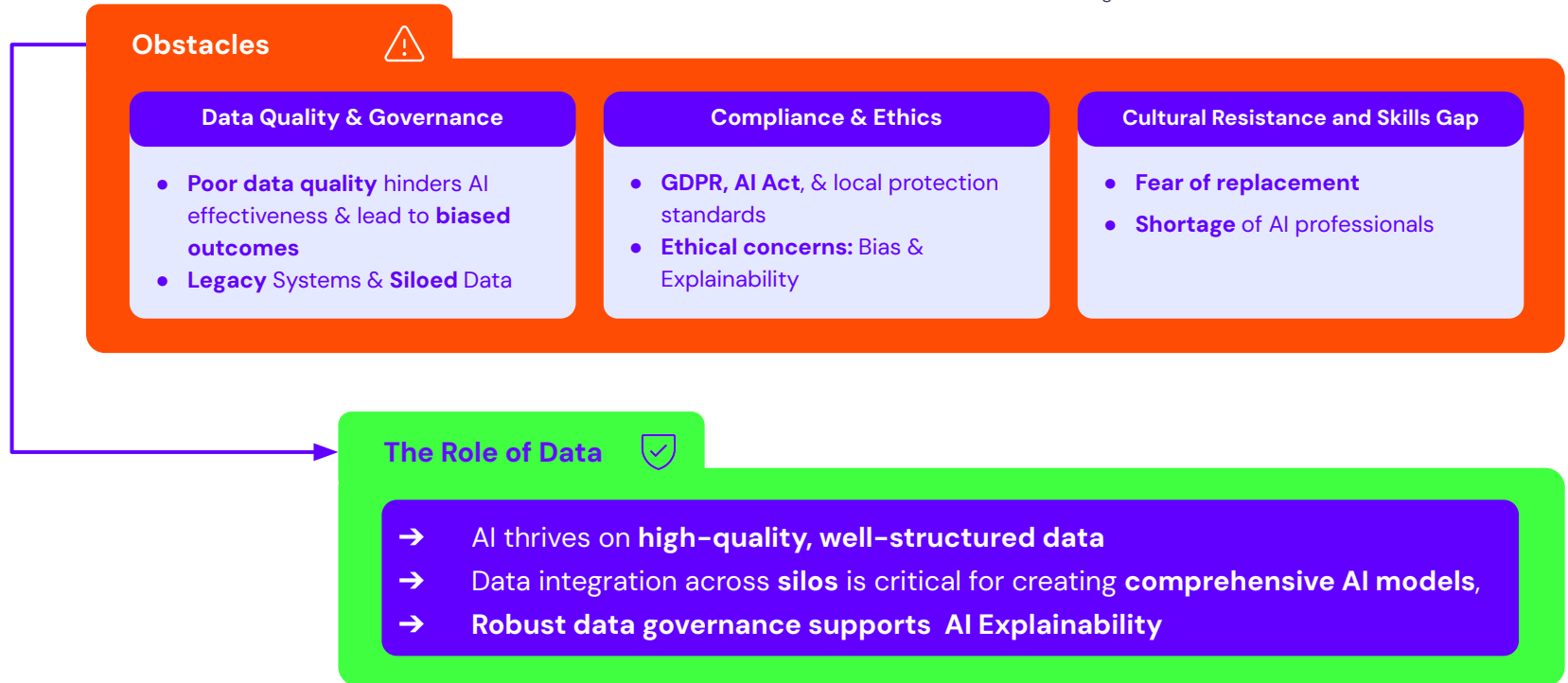
Customer Retention ✓

# Data & AI in Insurance

## Challenges & Hindering factors: The central role of Data

Often times, . . . , it's **limitations in the quality of data** platforms, master data management and data science that prevents from gaining the full value of AI

**Mike Helstrom** Principal, Insurance Technology Strategy  
Consulting KPMG in the US



5.

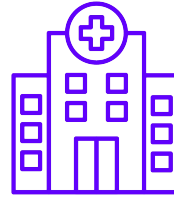
# Synthetic Data Applications

# Market & Applications

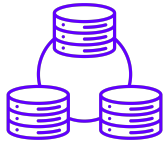
Enabling data leverage in Healthcare & Finance Industries



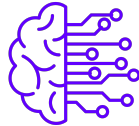
**Finance**



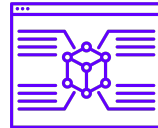
**Healthcare**



**Data  
sharing**



**AI model  
development**



**Product  
demos**



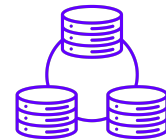
**Scenario  
simulations**



**Business  
Analytics**

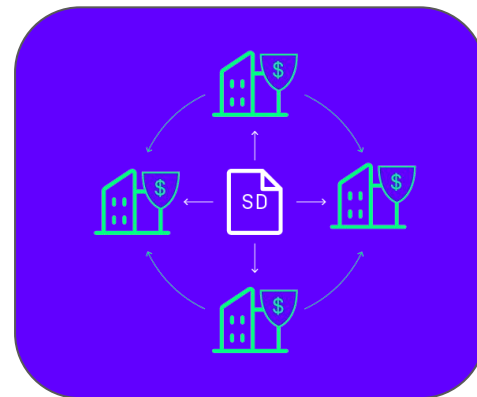


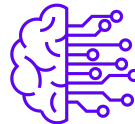
# Data Sharing (Intra/Inter Company)



## SYNTHETIC DATA ADDED VALUE:

- ✓ Enables the sharing of authentic customer data among stakeholders, eliminating costly data anonymization processes and reduces administrative burden;
- ✓ Enhances processes within the finance industry, preserving data privacy and regulation compliance (such as GDPR, HIPAA and CCPA);
- ✓ Leverage data, hindering innovation and collaboration within the ecosystem thanks to Unified data storage and management;
- ✓ More robust and accurate predictive model, thanks to enhanced data quality through data augmentation.





# AI Model Development

## SYNTHETIC DATA ADDED VALUE:

- ✓ Serves as a valuable resource for training AI models, offering benefits such as:
  - ❑ Scalability;
  - ❑ Privacy preservation;
  - ❑ Augmentation of limited datasets.
- ✓ Suitable solution for enhancing model performance and generalization.



# Enhancing add-on business applications: Scenario Simulation, Product Demo and Business Analytic



## SYNTHETIC DATA ADDED VALUE:



Enables **product seamless demonstrations**, accelerating development cycles and **allowing tests without exposing and relying on sensitive or limited data sources**.



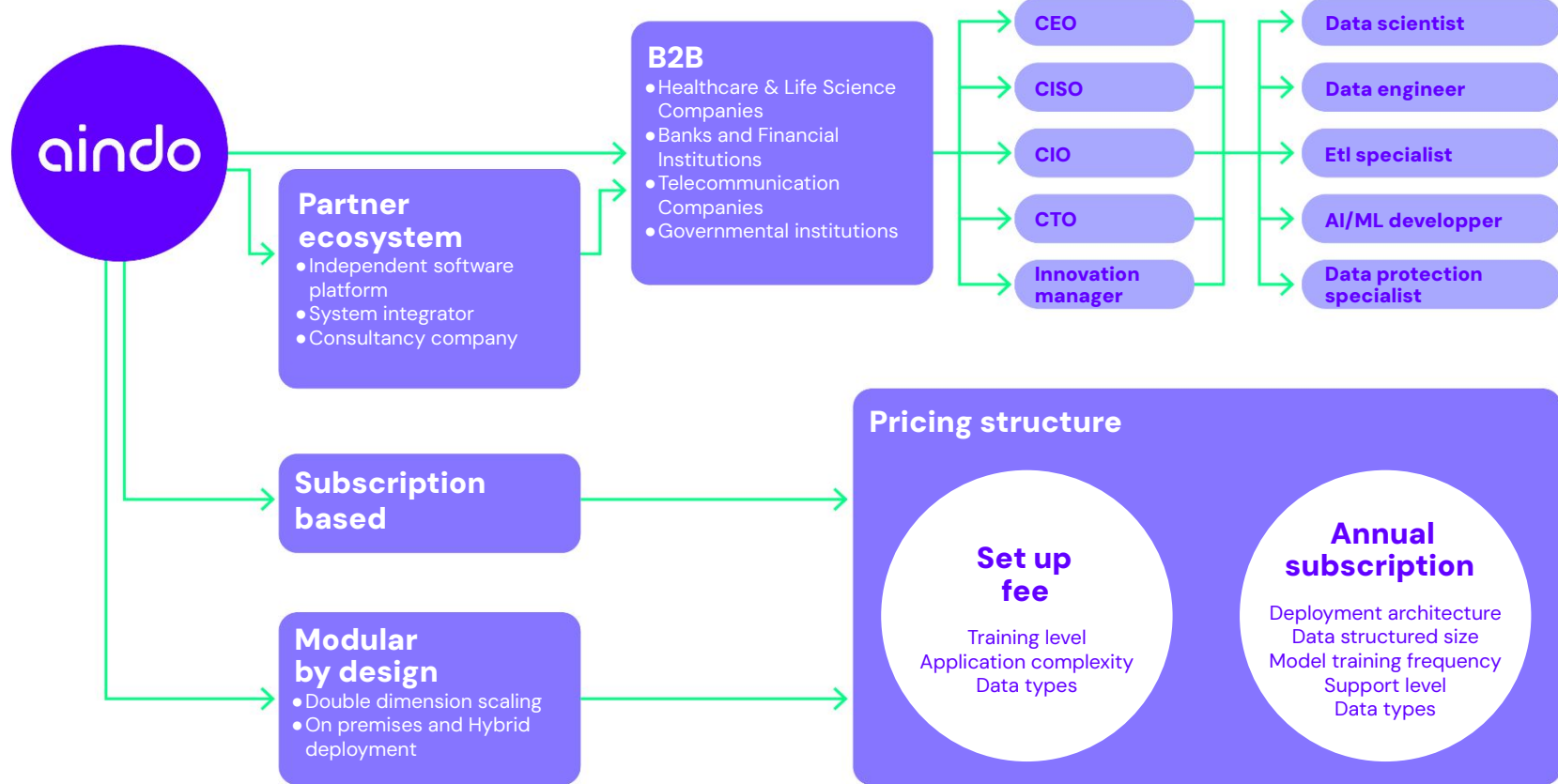
Enables gaining insights **equivalent to real data** and empowers **informed decision-making** and **integration into business intelligence tools**;



## 6.

# A Business Model for AI and Data in Europe

# Business Model





## 7.

# Interactive Discussion and Use Cases



# AI model compatibility for IVASS Regulatory Sandbox



## Concept



### POC

- Prove **synthetic data used for ML training** ensures adequate privacy and utility
- Verify **synthetic data's effectiveness in training two ML models**:
  - ☐ Forecast model to predict claims frequency
  - ☐ Forecast model to predict Conversion/Retention Rate

## Project



### STEP 1

MODEL  
COMPATIBILITY &  
DATA UTILITY

### STEP 2

PREDICTIVE MODEL  
PERFORMANCE  
ENHANCEMENT

### PLATFORM DEPLOYMENT

On-premises Aindo Web deployment

### RECORD MANAGEMENT

- Flat Table, 20 columns / 35k rows
- Flat table, 20 columns / 180k rows

## Outcomes step 1



### KPI ACHIEVED

Similarity score > 90%



Privacy score > 95%



Model Compatibility (Data Utility)



### ADDED VALUE

- Data utility/privacy preservation
- Enhancement of AI/ML model training

# VYV Group: AI model compatibility success story

## Concept

### POC

#### Measure:

- Synthetic data **utility loss vs. real data** (from a dental consumption study already carried out)

#### Assess:

- Whether synthetic data provides **comparable results without personal data constraints**

## Project

### STEP 1

SYNTHETIC  
DATA  
GENERATION

### STEP 2

SYNTHETIC  
DENTAL STUDY  
CREATION

### STEP 3

SYNTHETIC vs.  
REAL DATA  
STUDY  
COMPARISON

### PLATFORM DEPLOYMENT

SDK license integrated within the data pipeline

### RECORD MANAGEMENT

- Two Relational Tables:
- 5 columns / 20M rows
  - 2 columns / 1M rows

## Outcomes

### KPI ACHIEVED

Model Compatibility (Data Utility) 

Similarity score > 90% 

Privacy score > 95% 

Up to < 75% for Time to Data 

### ADDED VALUE

- Regulatory Compliance
- Operational time savings



insiel

# Enabling the creation of the Data Catalog in PA-Healthcare for secure data-sharing

## Business Problem

- Develop and manage Regional Health Data Catalogs:
- Need of strict adherence to privacy regulations, data security, governance, and ethical standards
- **Limitations of Legacy Anonymization Technologies:** legacy tool are impractical because they limit the utility of the data

## Solution

- Insiel developed and managed a synthetic data catalog for internal and external sharing using their technology
- Started with library SDK transitioning into platform for intuitive usability

## Value

- Created market for inaccessible healthcare data to drive internal and external collaboration
- Reduce time-to-data for research purposes for common health benefits
- Avoid potential data leaks and non-compliance with privacy regulations

# Real World Evidence (RWE) Development



for an undisclosed  
leading  
Pharmaceutical  
company

## Business Problem

- **Obtaining real-world evidence (RWE) is time-consuming:**
  - ❑ Obtaining real-world data (RWD) is an intensive process involving privacy compliance protocols, extensive permissions, and data curation.
- **RWE quality varies considerably:**
  - ❑ RWD is often siloed, hindering comprehensive insights.
  - ❑ RWD may also be static, not reflecting current unobserved variables, or lacking crucial information.
  - ❑ Traditional de-identification methods rely on information destruction (e.g. perturbation).

## Solution

- **Unlock rapid, secure data access:**
  - ❑ Synthetic data is directly available, compliant, and curated. This allows for immediate RWE development opportunities.
- **Access comprehensive, current information:**
  - ❑ Integrate siloed data into one single, comprehensive synthetic data lake.
  - ❑ Create synthetic data based on the most recent RWD, accurately capturing the current research environment.
  - ❑ Avoid information destruction through traditional de-identification.

## Value

- **Accelerated research:** Facilitate faster, more comprehensive RWE studies, accelerating research timelines.
- **Privacy-first approach:** Maintain compliance while enabling broad access to critical healthcare data.
- **Improved data quality:** Generate high-quality evidence based on comprehensive, up-to-date, and accurate data.



# Future Roadmap



# Next Steps: Expanding Synthetic Data's Role

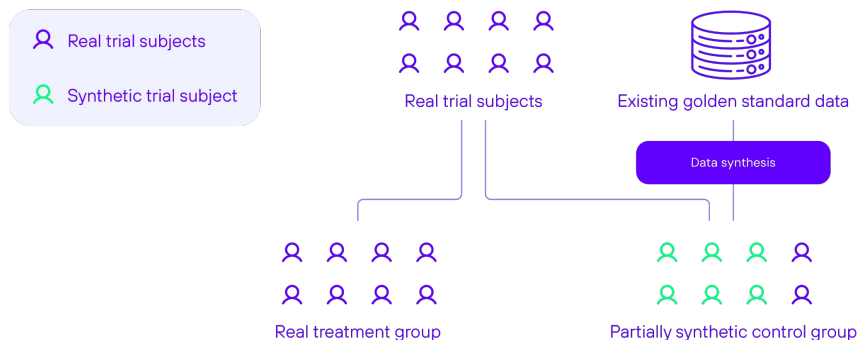
## Clinical trials with fewer control subjects

### Challenge

Obtaining clinical trial subjects is costly and time consuming, leading to long time-to-market for pivotal treatments.

### Solution

Partially synthetic control groups can reduce the number of real trial subjects needed. This streamlines the trials, leading to efficient access to treatments.



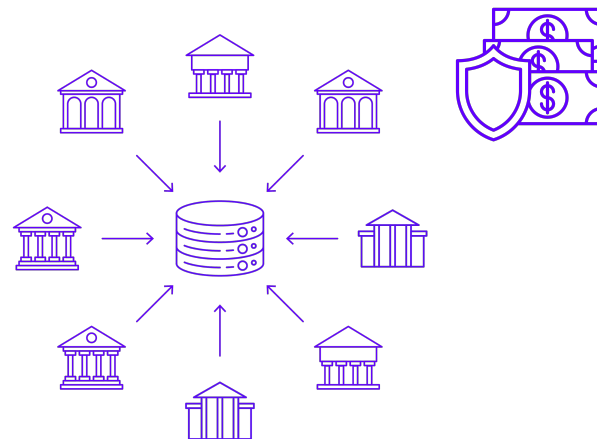
## Saving & Investment Union strategy enabler

### Challenge

SIU initiative is hindered by restrictions on data sharing, limiting transparency and market integration

### Solution

Synthetic data enables secure, privacy-compliant data exchange, fostering a unified capital market strategy





# Future Roadmap

## Next steps for strengthening privacy measures and industry impact.

Technology under evaluation by **CNIL**

Initiating engagement with the **aepd**

Active participation in **key data protection events**, including **Privacy Symposium** and **CPDP**

Achieving Financial KPIs & securing the next Funding Round

Continuous Accademica collaboration

Working with **EMA** for Scientific Advice to establish synthetic data as a standard for Synthetic Control Arms

**CNIL**

**aepd**  
agencia  
española  
protección  
datos

**PRIVACY  
SYMPOSIUM**

**EMA**  
EUROPEAN MEDICINES AGENCY



# Final Remarks

Q&A  
Q: What are the key challenges in implementing synthetic data?  
A: The main challenges are ensuring the synthetic data is of high quality, protecting privacy, and ensuring it is representative of the real data. It also requires a robust legal and ethical framework.  
Q: How can we ensure the quality of synthetic data?  
A: Quality can be ensured by using advanced generative models, such as Generative Adversarial Networks (GANs) or Variational Autoencoders (VAEs), and by implementing rigorous validation and testing procedures.  
Q: What are the privacy concerns with synthetic data?  
A: While synthetic data is designed to protect privacy, there is still a risk of re-identification if the data is not properly anonymized or if it is too similar to the real data. Strong privacy laws and regulations are essential.  
Q: How can synthetic data be used in healthcare?  
A: Synthetic data can be used for medical research, drug development, and clinical trials, allowing researchers to study rare diseases and test new treatments without the need for large amounts of real patient data.  
Q: What are the ethical considerations of synthetic data?  
A: Ethical considerations include ensuring transparency, accountability, and fairness. It is important to consider the potential for bias and discrimination in the data and to establish clear guidelines for its use.

- ❑ AI development is key to Europe's competitiveness but must prioritize **safety and data privacy**, especially in **regulated sectors like healthcare and finance**.
- ❑ **Synthetic data is the most advanced solution** for protecting consumer data while enabling responsible AI use.
- ❑ Privacy evaluation must **move beyond legacy standards**, adopting more effective assessment methods.
- ❑ **European certifications and standards** are essential for ensuring **trust, accountability, and safe AI adoption**.
- ❑ **Education and training** are crucial to raising awareness and driving **data-driven innovation**.

# Q&A Session

Thank you for your attention!

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