Machine learning in the official statistics production process

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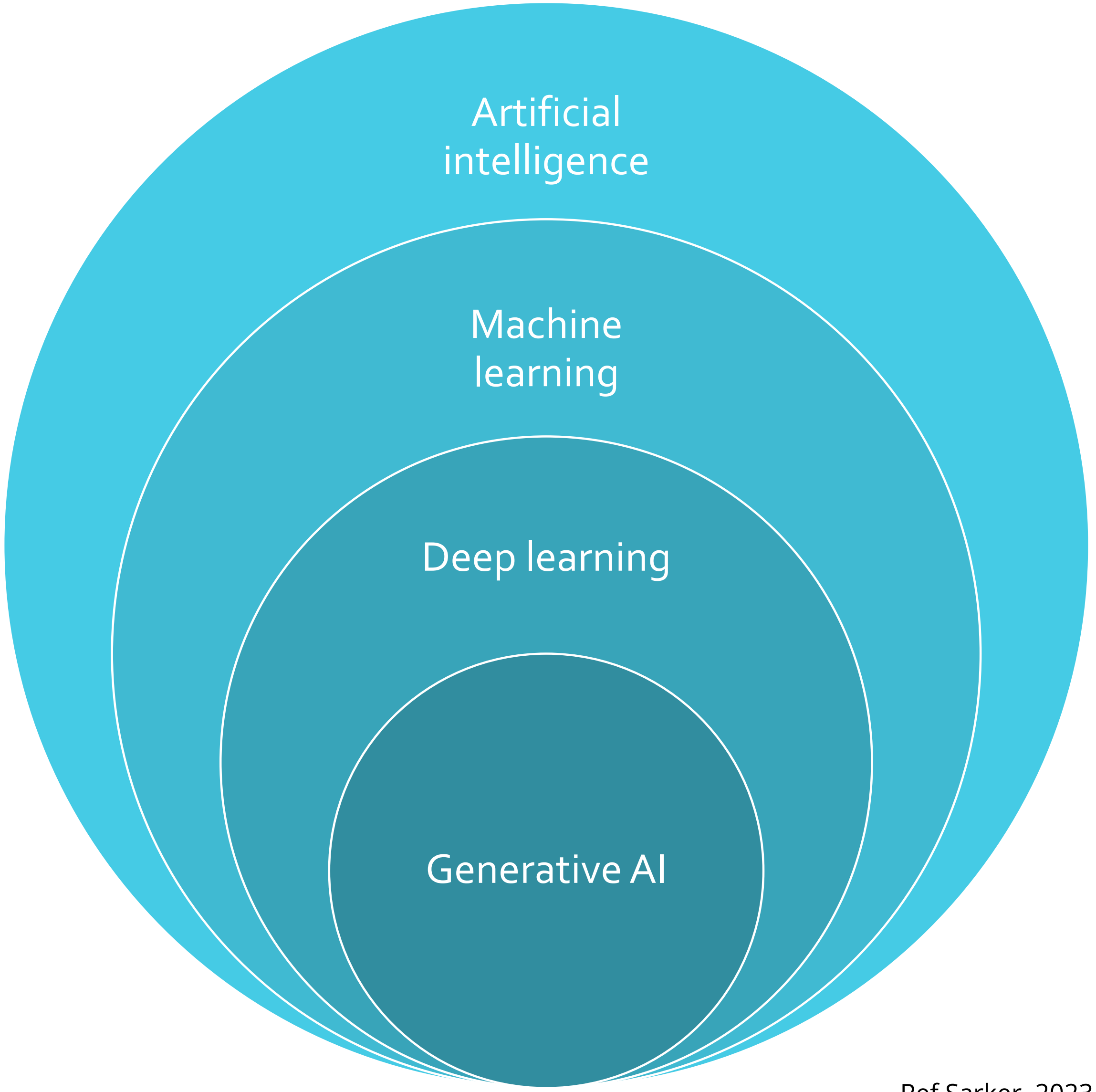
I. Definition of machine learning (ML) and relation to concepts of artificial intelligence (AI)

Definition of machine learning (ML) and relation to concepts of artificial intelligence (AI)



Ref Sarker, 2023
https://doi.org/10.1007/s42979-021-00815-1

Definition of machine learning (ML) and artificial intelligence (AI)

Artificial Intelligence (AI) – Any techniques that enables computers to mimic human intelligence. Includes machine learning

Machine learning (ML)– techniques that enable machines to improve tasks with experience. Includes deep learning

Deep learning – subset of machine learning based on neural networks that permit a machine to train itself to perform a task

Explainable AI

Generative AI

Unexplainable AI

Question is not what type of AI has been used, but how responsibly it is been used, communicated and explained as well as how risks are assessed and monitored.

Incomprehensibility AI

Ref. Yampolskiy 2020 DOI: [10.1142/S2705078520500150]

Definition of artificial intelligence (AI) by AI HLEG

AI is ...

AI is ...

"The use of algorithms. The term 'algorithm' refers to a specific instruction for solving a problem or performing a calculation."

"The imitation of all human intellectual abilities by computers."

"The imitation of various complex human skills by machines."

"Technology that can function appropriately and with foresight in its environment."

"Systems that display intelligent behaviour by analysing their environment and taking actions – with some degree of autonomy – to achieve specific goals."

Various definitions of AI

Bostrom,N director of the Oxford Institute for Internet Governance:
"**AI includes anything that impresses us at any given time.**
Once we are no longer impressed, we simply call it software."

Definition of artificial intelligence & machine learning

High-Level Expert Group on **Artificial Intelligence** (AI HLEG) of the European Commission (EC):
"AI is Systems that display intelligent behaviour by analysing their environment and taking actions – with some degree of autonomy – to achieve specific goals.

Artificial intelligence:
AI is equated with algorithms.
AI stands for the imitation by computers of the intelligence inherent in humans.
AI is an imitation or simulation of something we do not yet fully understand ourselves: beyond human intelligence.
(ref. Sheikh, Prins, Schrivers (2023) https://doi.org/10.1007/978-3-031-21448-6_2

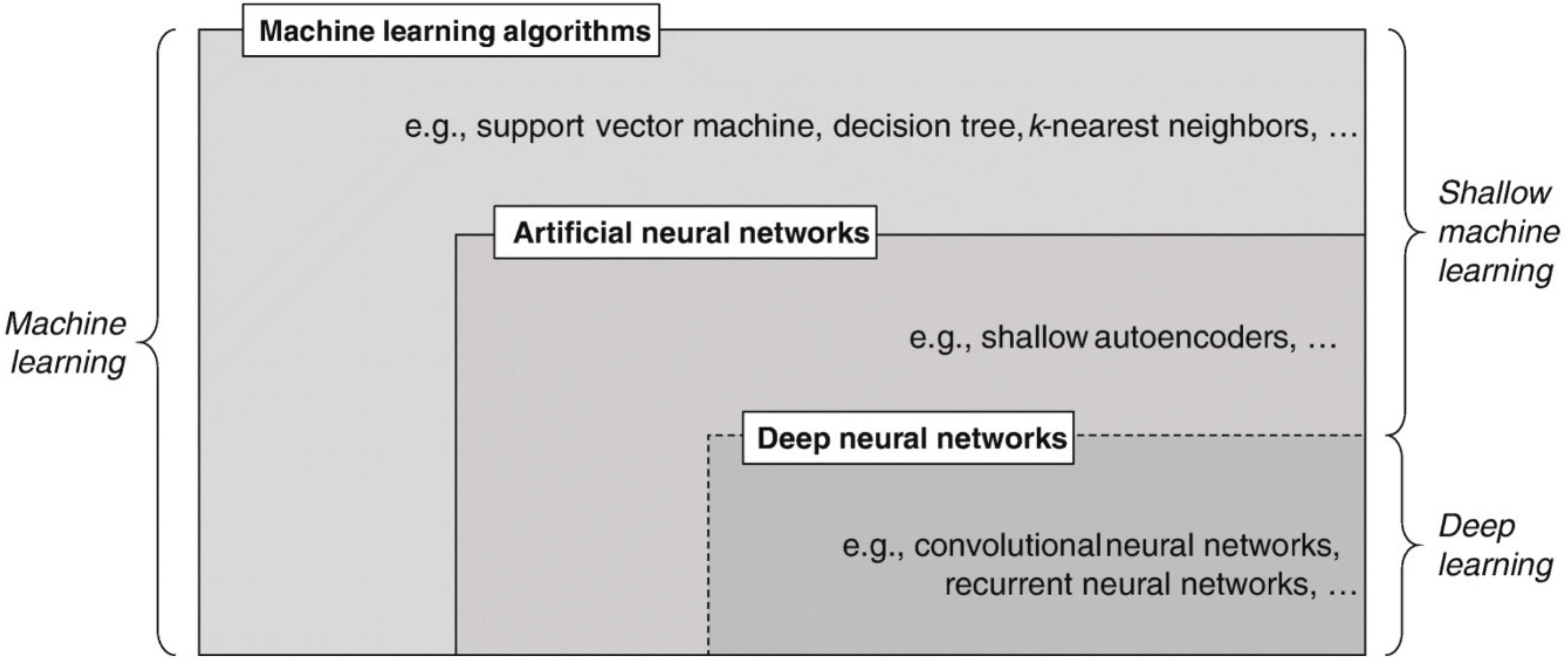
Further discussion in open course: https://www.elementsofai.com/

UNECE (2021): **Machine learning** is a "field of study that gives computer the ability to learn without explicitly being programmed"

Hierarchical relationship between machine learning algorithms, artificial neural networks, and deep neural networks

by Janiesch, Zschech & Heinrich (2021)
https://doi.org/10.1007/s12525-021-00475-2

From: Machine learning and deep learning

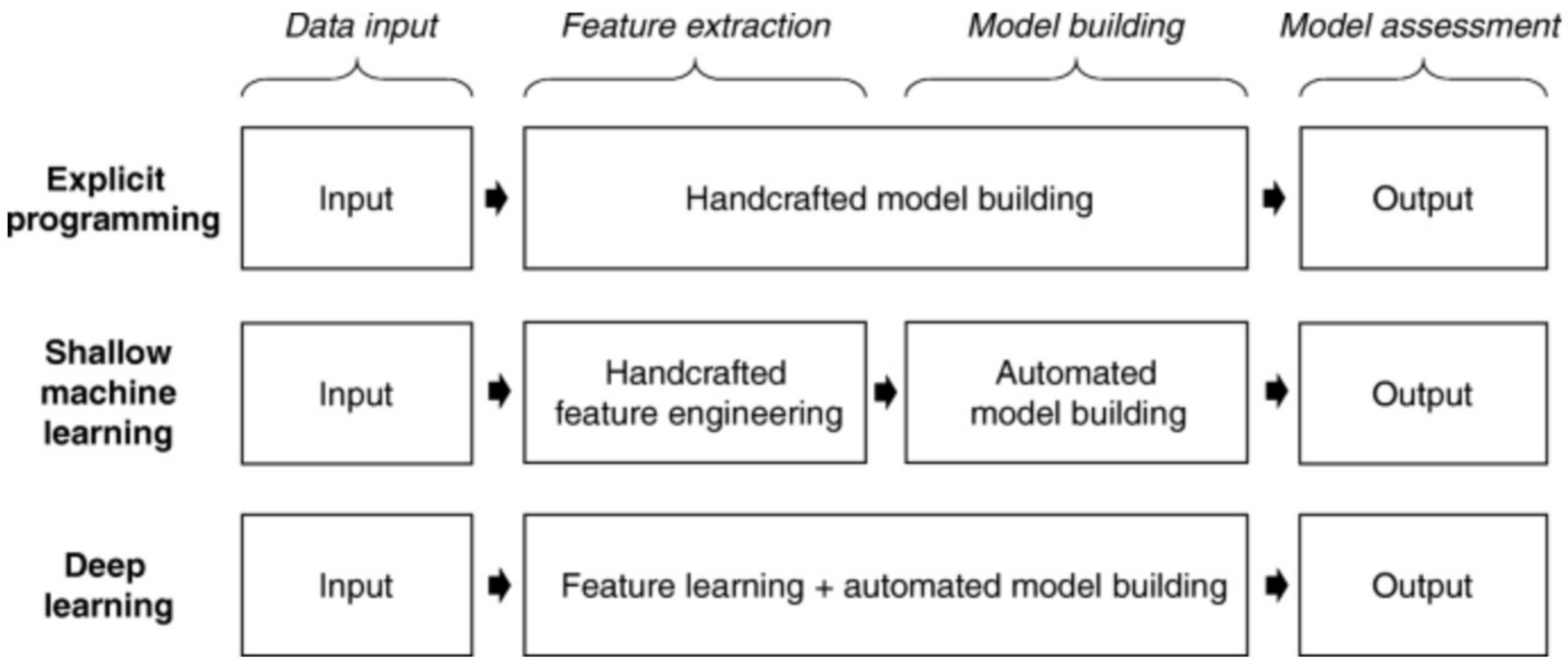


Venn diagram of machine learning concepts and classes (inspired by Goodfellow et al. 2016, p. 9)

Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. The MIT Press.

Framework on the process of analytical model building for explicit programming, shallow ML, and DL

by Janiesch, Zschech & Heinrich (2021)
https://doi.org/10.1007/s12525-021-00475-2



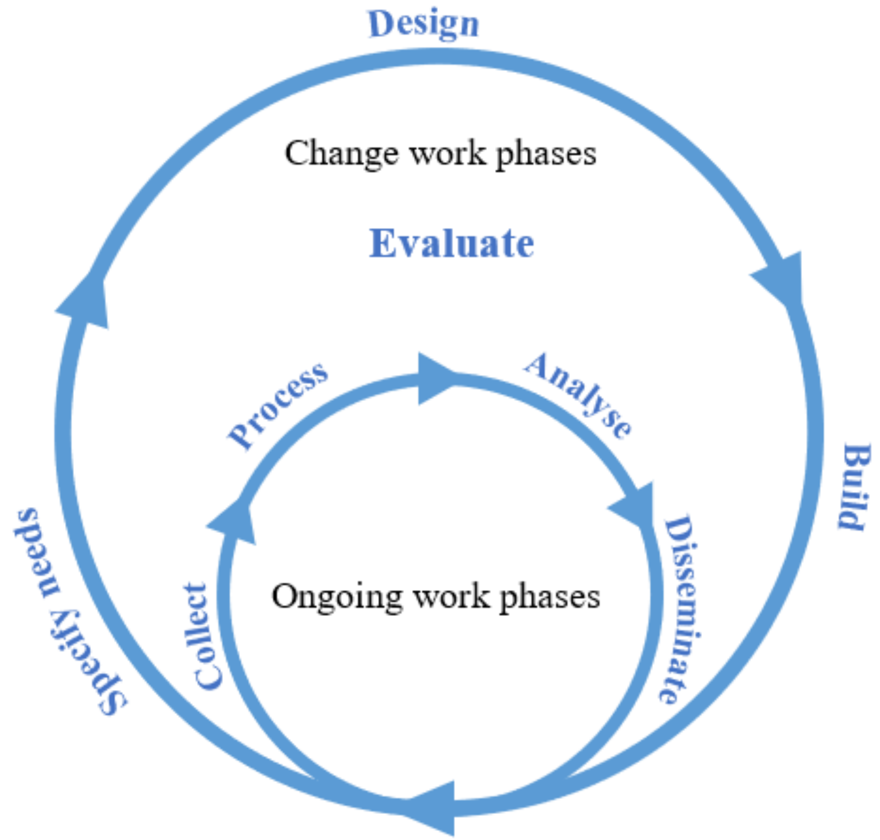
Process of analytical model building (inspired by Goodfellow et al. 2016, p. 10)

Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. The MIT Press.

II. Aligning ML methods into GSBPM process

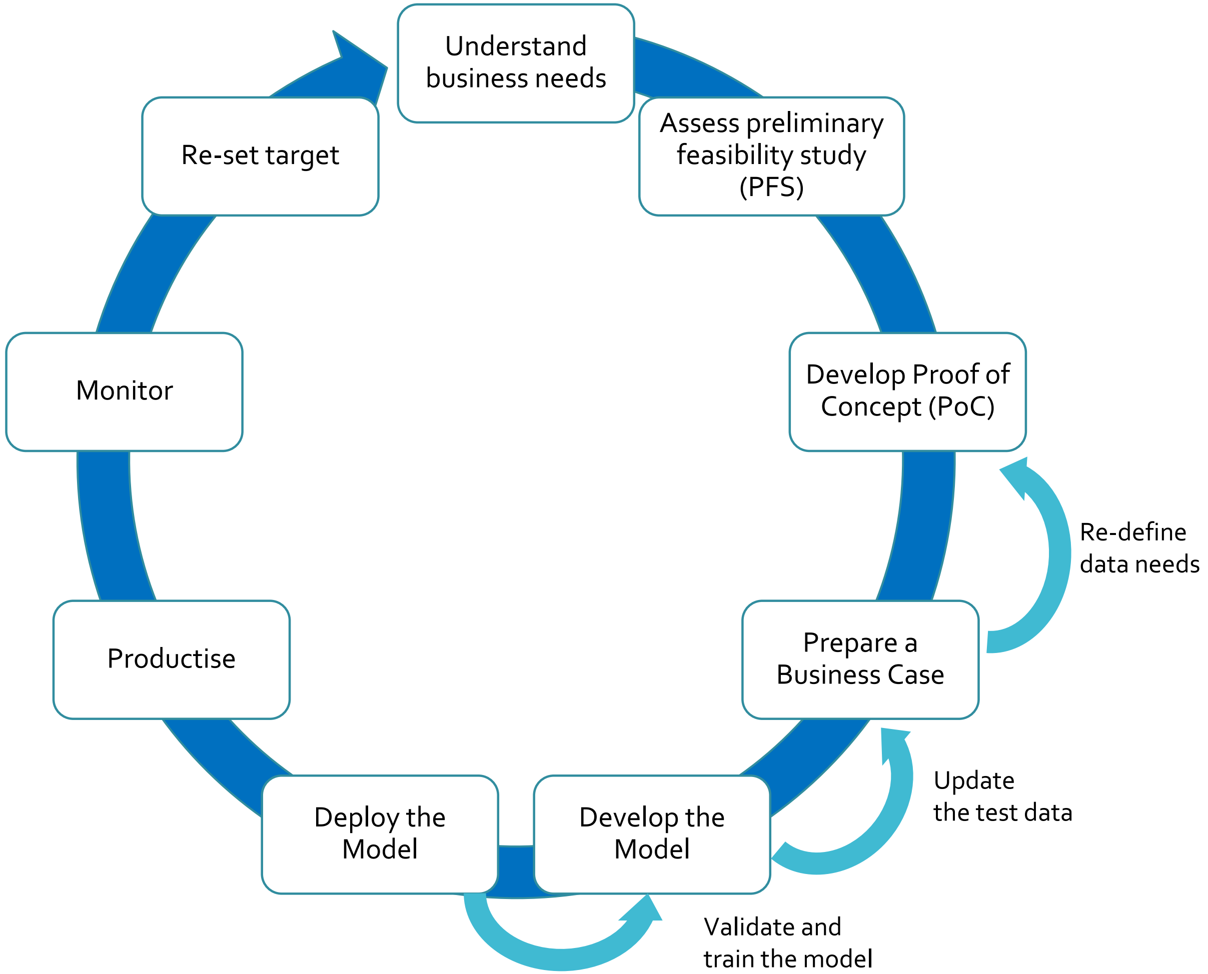
Comparison of generic statistical business production model and data analytics & ML development process

Generic Statistics Business Process Model - GSBPM 5.1



UNECE for GSBPM 5.1 (2019)

ML development process – ref. UNECE ML 4 OS (2021)



Generic Statistical Business Production Model GSBPM & Use of ML

Overarching Processes

Specify needs	Design	Build	Collect	Process	Analyse	Disseminate	Evaluate
1.1 Identify needs	2.1 Design outputs	3.1 Reuse or build collection instruments	4.1 Create frame and select sample	5.1 Integrate data	6.1 Prepare draft outputs	7.1 Update output systems	8.1 Gather evaluation inputs
1.2 Consult and confirm needs	2.2 Design variable descriptions	3.2 Reuse or build processing and analysis components	4.2 Set up collection	5.2 Classify and code	6.2 Validate outputs	7.2 Produce dissemination products	8.2 Conduct evaluation
1.3 Establish output objectives	2.3 Design collection	3.3 Reuse or build dissemination components	4.3 Run collection	5.3 Review and validate	6.3 Interpret and explain outputs	7.3 Manage release of dissemination products	8.3 Agree an action plan
1.4 Identify concepts	2.4 Design frame and sample	3.4 Configure workflows	4.4 Finalise collection	5.4 Edit and impute	6.4 Apply disclosure control	7.4 Promote dissemination products	
1.5 Check data availability	2.5 Design processing and analysis	3.5 Test production systems		5.5 Derive new variables and units	6.5 Finalise outputs	7.5 Manage user support	
1.6 Prepare and submit business case	2.6 Design production systems and workflow	3.6 Test statistical business process		5.6 Calculate weights			
		3.7 Finalise production systems		5.7 Calculate aggregates			
				5.8 Finalise data files			

UNECE for GSBPM 5.1 (2019)

Generic Statistical Business Production Model GSBPM & Use of ML

Overarching Processes							
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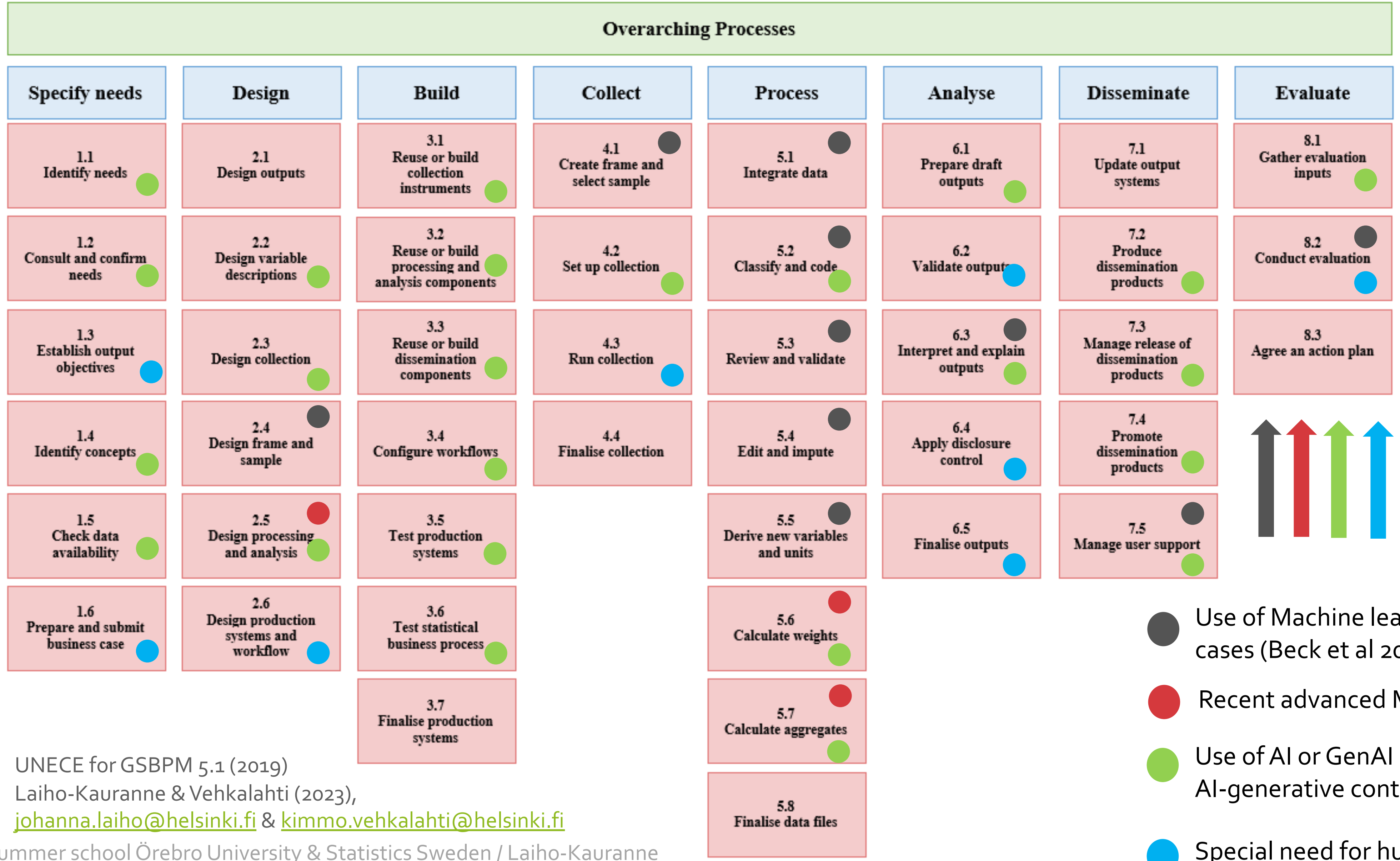
- ✓ Higher efficiency
- ✓ Effectiveness
- ✓ Improved cost efficiency

● Use of Machine learning ML cases (Beck et al 2018)

UNECE for GSBPM 5.1 (2019)

Generic Statistical Business Production Model GSBPM
- tracked use of ML, and potential AI or Gen AI use steps for surveys



- ✓ Higher efficiency
- ✓ Effectiveness
- ✓ Improved cost efficiency

Use of Machine learning ML cases (Beck et al 2018)

Recent advanced ML deployment

Use of AI or GenAI cases, excluding AI-generative content (AIGC)

Special need for human centric AI

UNECE for GSBPM 5.1 (2019)
Laiho-Kauranne & Vehkalahti (2023),
johanna.laiho@helsinki.fi & kimmo.vehkalahti@helsinki.fi

III. Current challenges of statistical surveys as use cases for ML

DESIGN

DATA COLLECTION & PROCESS

DISSEMINATION

Transform challenges of statistical surveys into use cases for ML

Design	Collection & Process	Dissemination

Design

- Societies & economy in transition: Concepts become outdated risking *relevance*
- Maintaining relevance impacts *comparability*.
- International reach for new definitions: *timeliness of comparable information*.
-

Collection & Process

- Reduction in response rates to critically low levels impact *reliability* and *accuracy*
- Surveys maximising use of register data compromise *timeliness* and also *relevance* of information
- Auxiliary data requires resources to establish *interoperability*
- Structural changes may reduce *coherence*, unless time series are corrected.

Dissemination

- Concepts, themes and results can be misunderstood but also ignored, affecting *findability* and *accessibility*
- Public debate of results may affect *trust* and require unexpected allocation of resources
- One typical KPI of surveys is the volume of usage which via chatbots and other platforms may not be *measurable*.

Transform challenges of statistical surveys into use cases for ML II

Response rates have for long fallen and have reached critically low levels (Sturgis and Luff, 2021)

Buskirk and Kirchner (2020) provide examples of how traditional ML methods can improve efficiency in the survey process

Gelsema and Heuvel (2023) propose a framework for using generative language models to tailor statistics on the fly

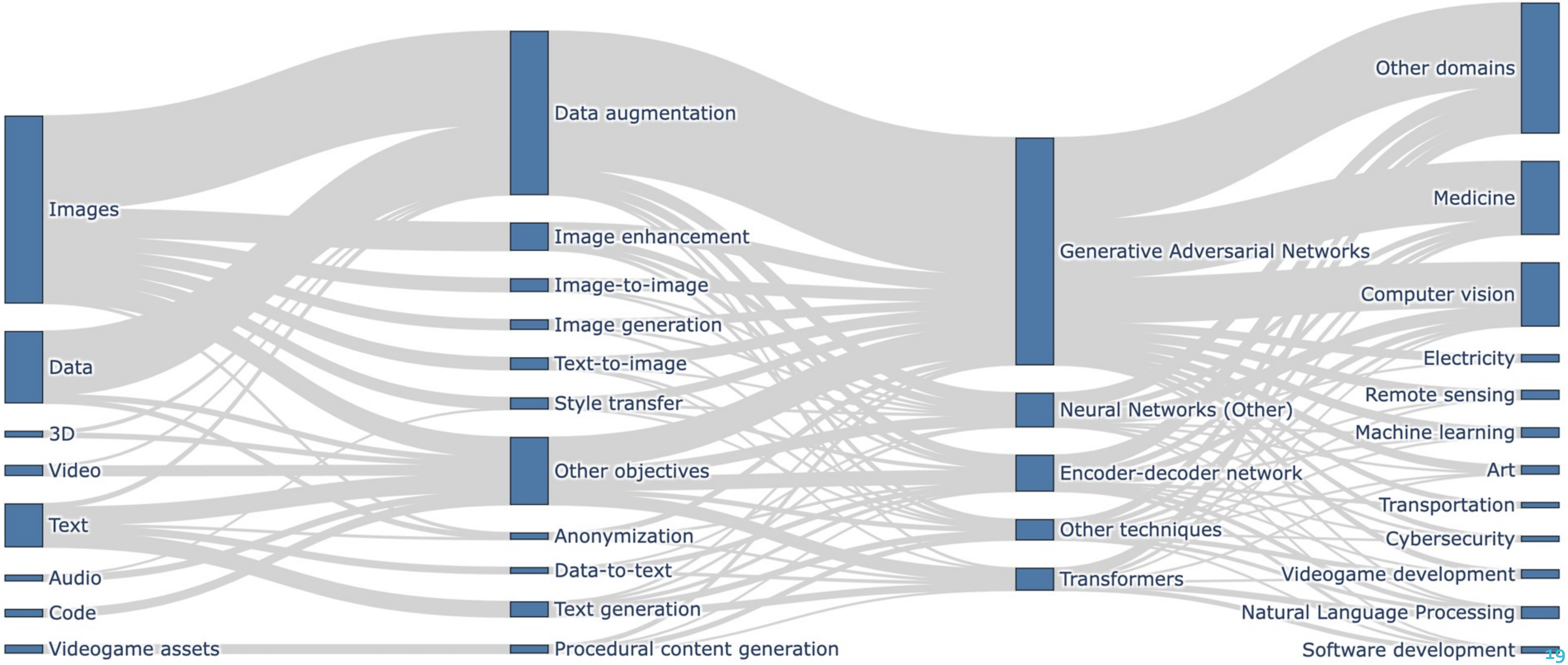
The future of surveys will depend on their adaptation to changing communication technology (Miller, 2017)

→ machine learning (ML) is seen as a key methodological enabler for achieving higher quality with lower costs

IV. Which challenges the deployment of ML can unlock? Can AI provide additional tools needed?

Meta-analysis by García-Peñalvo, Vázquez-Ingelmo (2023) studied how largely AI can be used and maps GenAI use cases

& define Generative AI as the production of previously unseen synthetic content, in any form and to support any task, through generative modeling.



Potential AI use cases for survey pain points I for selected GSBPM sub-processes

GSBPM Sub-process	Business value	Use of AI examples
1.2 Consult & confirm needs	Objective assessment of relevance of the identified needs clarifies & updates purpose, detect information gaps.	Text – Text generation
1.5 Check data availability	New innovative approaches and sources improve relevance	Data – Relevant data detection
1.6 Prepare and submit business case	GenAI evaluates business case with objective criticism	Text – Text generation
2.2 Designing variable descriptions	Respondents and users understand the concepts and information content as they are modernised to modern commonly used typology.	Text – Text generation, conversational elements
2.3 Design collection	Designing questionnaire / instruments to raise interest and increase response rates by tailoring motivation techniques and ad hoc capability to provide translations & script suggestions for presenting the survey	Video / Text / Audio – Style transfer, Data to text, Instrument / Questionnaire generation with large language models, Procedural content, Recommendation systems

Potential AI use cases for survey pain points II for selected GSBPM sub-processes

GSBPM Sub-process	Business value	Use of AI examples
2.5 Designing processing and analyses	Develop atomization of tasks and preprocessing routines	Text / Code / Image – Text / Code / Image generation
2.6 Design production and data flows	Survey design optimization Gen AI can make optimization suggestions	Image – Image generation
3.1 Reuse or build collection instruments	Optimize resources in assessing the need and redeveloping collection instruments and	Text / Code / Image – Text / Code / Image generation
3.6 Test statistical business process	Instead of conducting expensive tests GenAI can perform perceived responses by different types of respondents	Text / Data - Text generation / Data augmentation with diffusion models
4.2 Set up collection	Collection instrument final edits are suggested by GenAI	Text / Code – Code generation
4.3 Run collection	Data collection is assisted by optimizing contact touch points / contact attempts, tailoring approaches, ad hoc translations, complementary checks	Data / Text / Image – Sentiment analysis, Text generation LLM, (synonyms, explanations & translations), Converstational elements, Procedural content, Dynamic question ordering (DQO), Recommendation systems

Potential AI use cases for survey pain points III for selected GSBPM sub-processes

GSBPM Sub-process	Business value	Use of AI examples
6.1 Prepare draft outputs	Survey reporting is assessed to ensure quick reporting and objectively detect results to reflect to topical discussions and policies*	Data – Anomaly detection / Pattern recognition / Text generation
6.3 Interpret and explain outputs	Potentially controversial or easily misunderstood issues are detected & examined by humans to decide upon GenAI suggestions for understandable explanations	Data / Text –Text generation with neural networks and large language models for data cleaning, and detect inconsistencies
7.2 Produce dissemination products	Dissemination products can be generated with automation for target groups needs	Data / Text – Data augmentation / Text generation
7.4 Promote dissemination products	Develop innovative communication strategies for target groups	Text / Data - Data to text, Procedural content
7.5 Manage user support	Utilize conversational interfaces and virtual agents as front-end service	Text / Data - Data to text, Procedural content
8.1 & 8.2 Gather & Conduct evaluation	Evaluate all internal and external feedback and performance data with suggested action points	Text / Data – Report generation

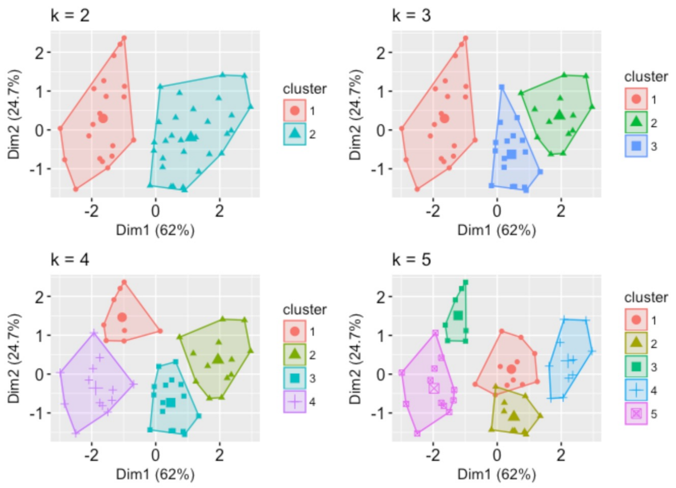
Machine learning techniques applied in official statistics

Cluster methods	Linear regression	Logistic regression	Decision trees	Random forests
Support vector machines (SVM)	Neural networks	Naïve Bayesian	Artificial neural networks (ANN)	Multi-layer Perceptron (MLP)
Convolutional Neural Networks (CNN)	Recurrent Neural Networks (RNN)	FastText	eXtrem Gradient boosting (XGBoost)	Deep learning

Cluster methods - ML for Official statistics, UNECE

Types of clustering methods:

- **K-Means** – K indicates the number of clusters user defines
- **MeanShift** - The algorithm automatically determines the number of clusters based on data
- **DBSCAN** – Density-Based Spatial Clustering of Applications with Noise assumes clusters are dense spaces in the region separated by lower-density regions
- **Hierarchical clustering** - Builds a hierarchy of clusters either bottom-up or top-down
- **BIRCH** - Balanced Iterative Hierarchical Based Clustering generates a summary of the information that the other clustering algorithms can utilize. Can be used for very large data sets



Source: https://uc-r.github.io/kmeans_clustering

Expected benefits from clustering methods

- save manual work ,
- increase timeliness, and
- reduce risk for human error

Cluster methods - ML for Official statistics

Algorithm name	Category	Function in R	Library in R
k-means	Partitional	*k-means*	stats
clara	Partitional	*clara*	cluster
hierarchical	Linkage	*agnes*	cluster
EM	Model-based	*mstep, estep*	mclust
hcmodel	Model-based	*hc*	mclust
spectral	Spectral methods	*specc*	kernlab
subspace	Based on subspaces	*hddc*	HDclassif
optics	Density	*optics*	dbscan
dbscan	Density	*dbscan*	dbscan

Source: Rodriguez et al (2019): Clustering algorithms: A comparative approach https://doi.org/10.1371/journal.pone.0210236

Promising examples of using of machine learning in statistics production call for holistics approach for deployment

Social statistics measuring poverty

Burger & van der Laan (2021):
SHAP method in poverty

Clustering local authorities

ONS Data and Analysis from Census:
Regional statistics:

Maintenance of register & reduction of manual work in production

ABS:
ML model for Address Register (AR) maintenance and automated image recognition

Editing and imputation – Hot Deck & multiple imputation

Statistics Sweden:
Imputation of occupation

Statistics Norway
Editing process

US Census Bureau :
Cluster analysis in Hot Deck

Statistics New Zealand Census microdata

Statistics Poland :
Survey on sports clubs

Coding & classification

UNECE ML report for OS:
industry, occupation, economic activity, injury & illness

Modelling for estimation

US Bureau of labor statistics:
State level expenditure

Flash/ Early estimates estimates

Statistics Norway:
Flash estimation using transaction data and purposive samples

Statistics Spain:
Early estimates for Industrial Turnover Index

Statistics Finland:
Early estimates for Turnover Index

Looking beyond statistical process into our reported statistics of use of AI

What can we learn from our respondents?

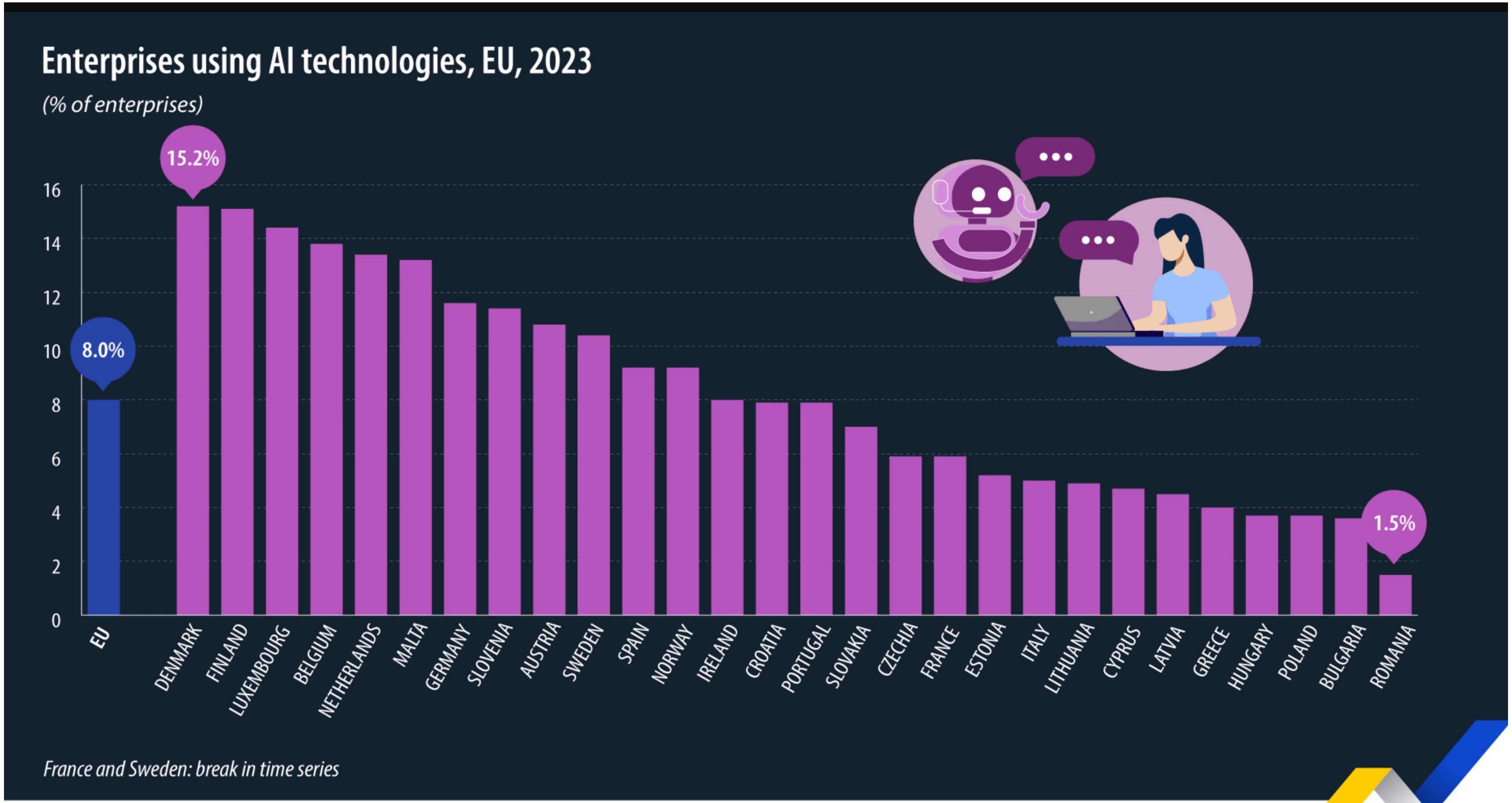
How is use of AI measured and reported in enterprise statistics?

Eurostat carries out statistics on enterprices using AI, namely artificial intelligence technologies:

- technologies analysing written language (text mining)
- technologies converting spoken language into a machine-readable format (speech recognition)
- technologies generating written or spoken language (natural language generation)
- technologies identifying objects or people based on images (image recognition, image processing)
- machine learning (e.g. deep learning) for data analysis
- technologies automating different workflows or assisting in decision-making (AI based software robotic process automation)
- technologies enabling machines to physically move by observing their surroundings and taking autonomous decisions.

What % of companies would you expect to have used AI (as defined above) last year in 2023?

Eurostat statistics on Enterprises using AI technologies in EU in 2023



Compared with 2021, use of AI technologies increased by 0.4 % by 2023

... Which is very low in contrast to exponential growth of GenAI

eurostat

Source: 2023 EU survey on ICT usage and e-commerce in enterprises & https://ec.europa.eu/eurostat/en/web/products-eurostat-news/w/ddn-20240529-2

How is use of AI measured and reported in enterprise statistics?

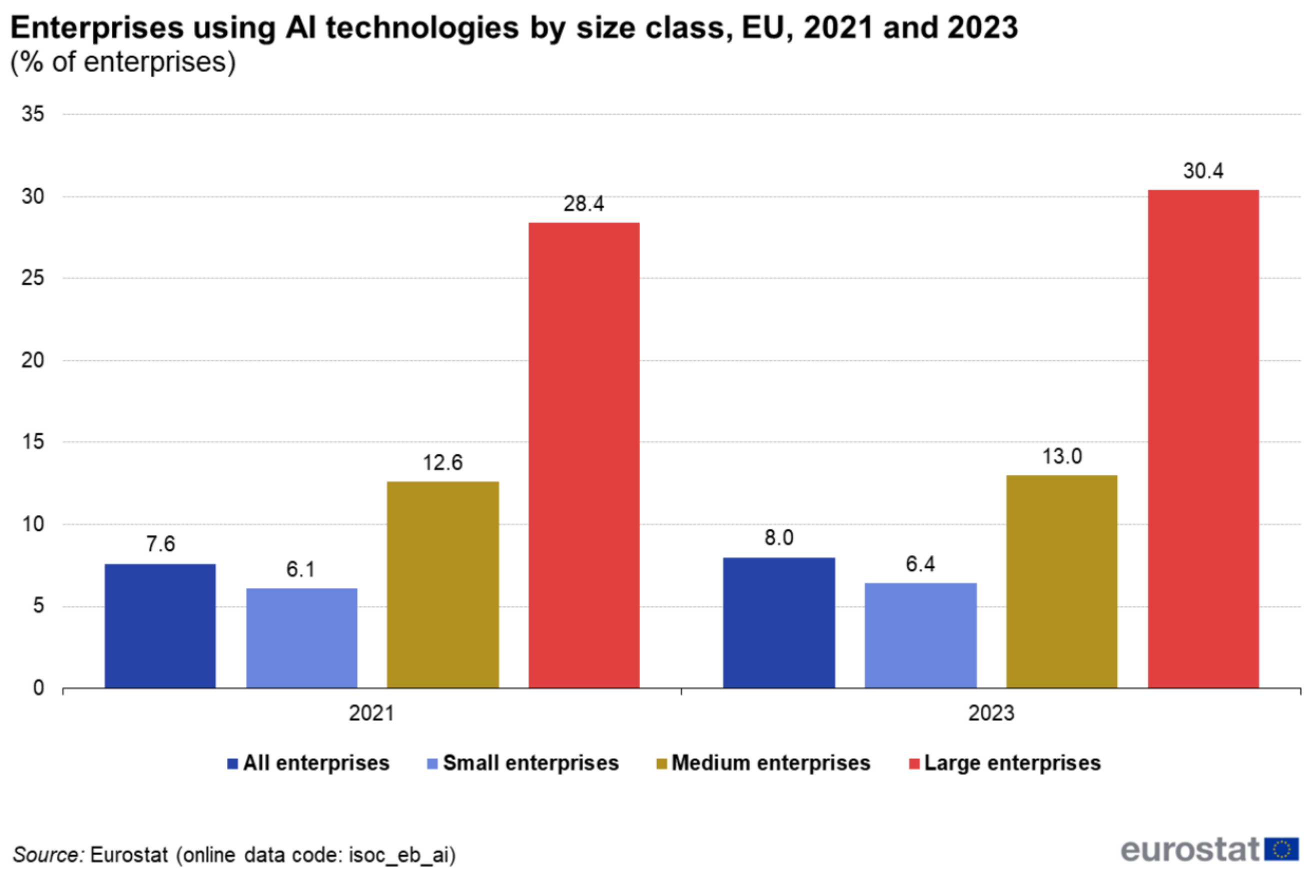


Figure 1: Enterprises using AI technologies by size class, EU, 2021 and 2023

(% of enterprises)

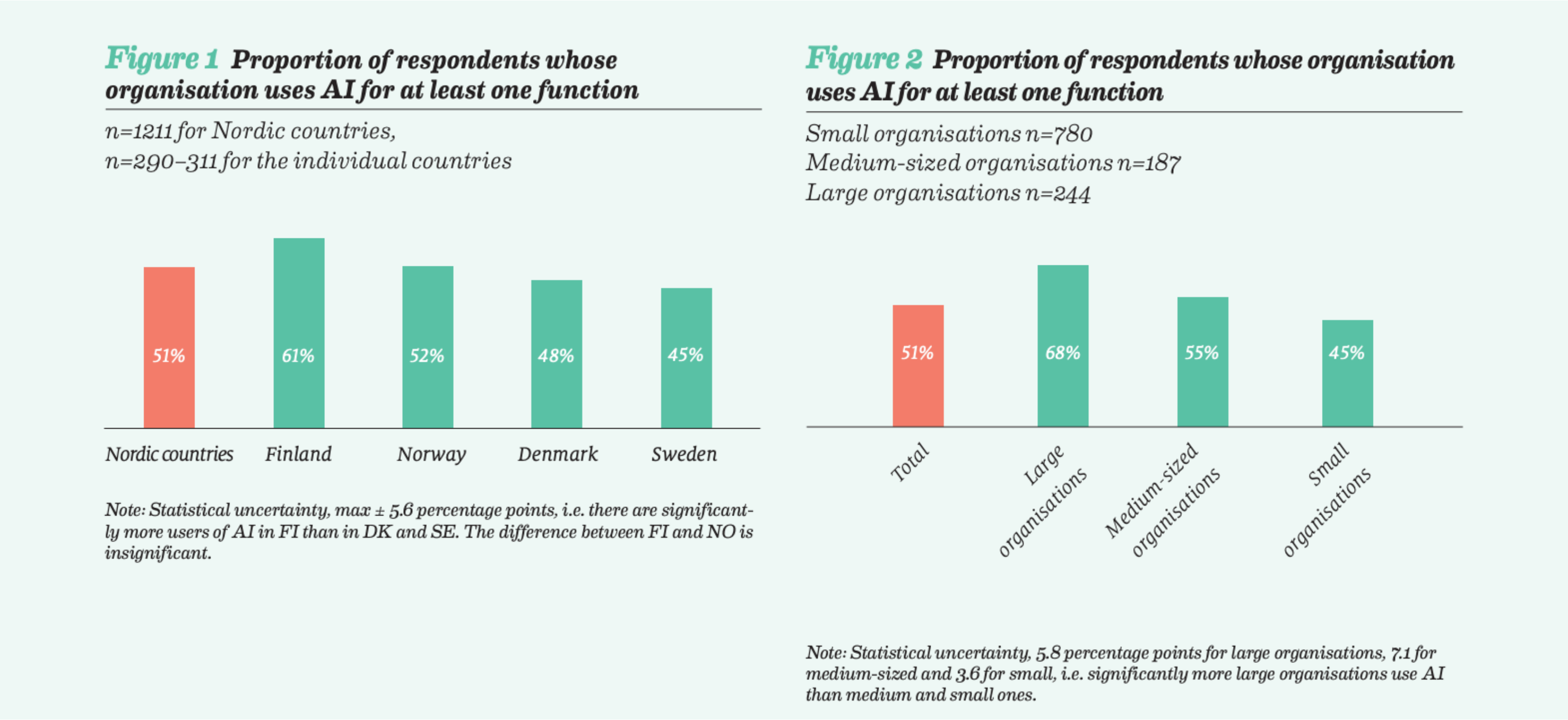
Source: Eurostat (isoc_eb_ai)

https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Use_of_artificial_intelligence_in_enterprises

Use of AI in Nordic organizations statistics by Finansförbundet

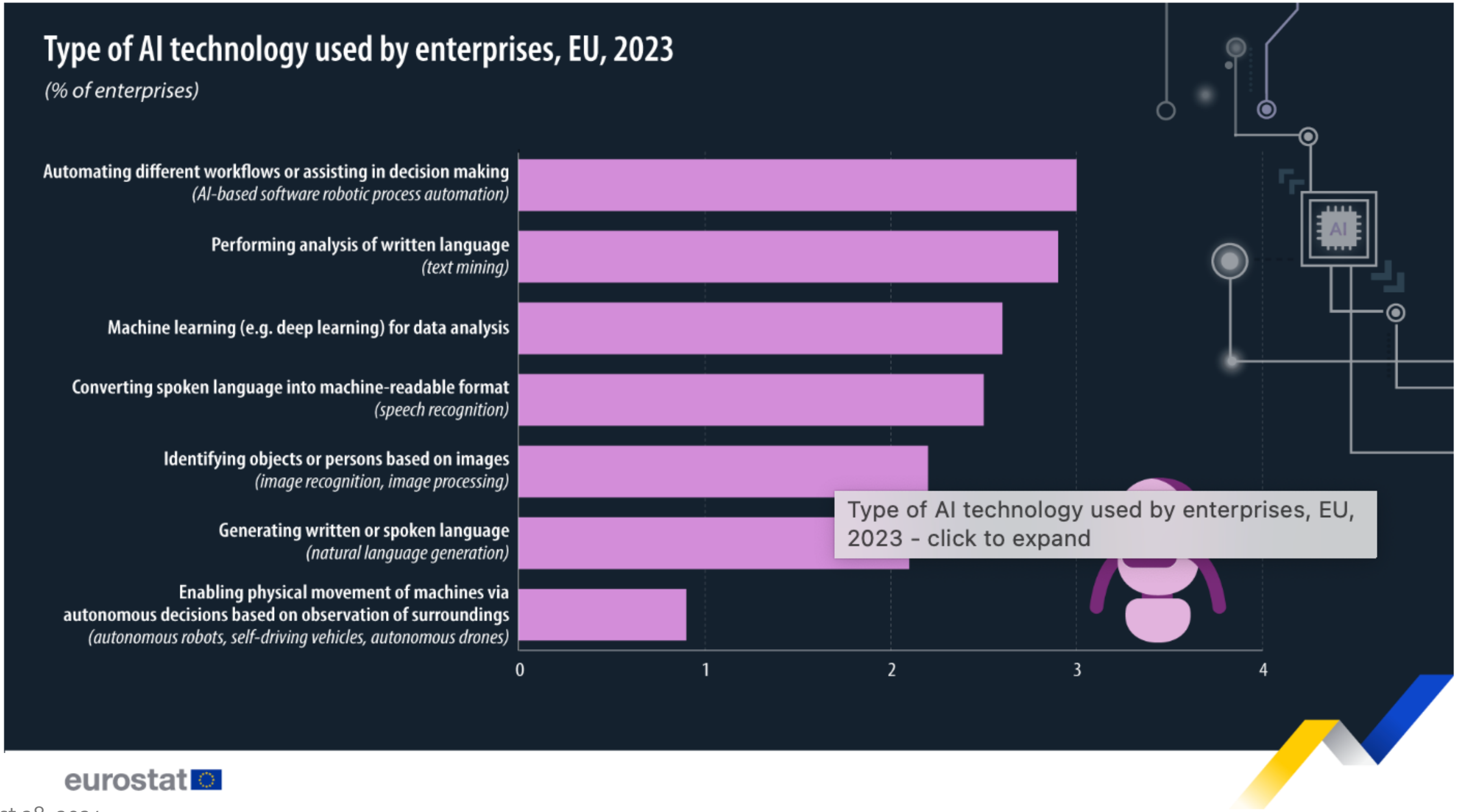
Finansförbundet studied 1,200 Nordic leaders in the private and public sectors in 2023:

- Use of AI ranges from 61% in Finland to 52% in Norway, 48% in Denmark and 45% in Sweden.
- Most frequent use is 'text generation' (31%), indicating GenAI, is making headway in the Nordic Region.
- Nordic organisations typically use AI for operational purposes: automating processes or improving products and services.
- Over half have worked with AI, but only 15% have drawn up a strategy for its use.



Sources: https://finansforbundet.dk/media/2z4mgccl/ai-i-norden_engelsk.pdf

Eurostat statistics on Enterprises using AI technologies in EU in 2023



Use of AI technologies in enterprises are similar to those that would have technology potential in statistics production

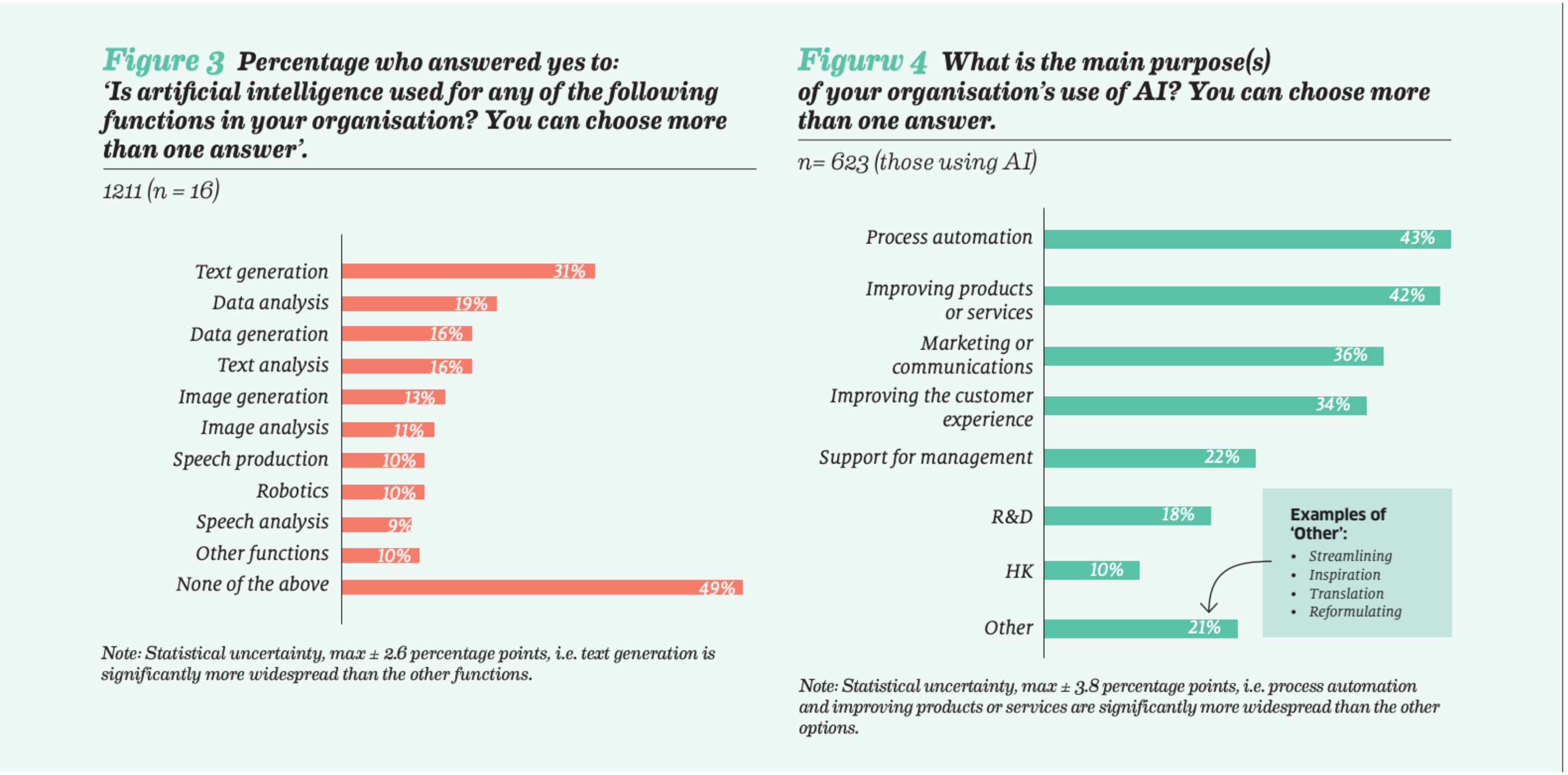
Source: 2023 EU survey on ICT usage and e-commerce in enterprises

https://ec.europa.eu/eurostat/en/web/products-eurostat-news/w/ddn-20240529-2

Use of AI in Nordic organizations statistics by Finansförbundet

Finansförbundet survey on Nordic leaders in the private and public sectors in 2023:

- Text generation, data analysis, data generation, text and image analysis are most typical functions of use
- Process automation and improvement of products and service are the main purposes for use



Sources: https://finansforbundet.dk/media/2z4mgccl/ai-i-norden_engelsk.pdf

How do we measure and report of AI in enterprise statistics on use of AI?

- Vrs. Stanford University's 'AI Index 2023' and McKinsey's 'The State of AI in 2023' show that 50% of organisations worldwide use AI.
- Measurement error & in which source?
- Problem related with wording, data collection, salience of response?
- Would we receive the same result if we asked the same question from representative sample of employees, one selected person, or leader of the organization e.g.:
  "Do you use AI in your work"?
- How much of usage of natural language generation is under-reported or not even measured in enterprices so that the person responding to official statistical survey is able to respond on behalf of other employees and business units?
- Cipollone, P (2024) Artificial intelligence: a central bank's view – link
  refer to Robert Solow: "You can see the computer age everywhere but in the productivity statistics." … "Might we see another Solow paradox emerge in the context of AI?"

V. Acceptability of using of machine learning & AI in official statistics

Plausible concerns of survey methodologist vs potential use of AI

Surveys tend to be by nature conservative to be trusted for maintaining high quality. Concerns should be addressed and both benefits and risks evaluated and continuously monitored. Concerns relate to:

- Bias and fairness of results
- Data privacy and data security
- Quality control
- Response authenticity
- Lack of contextual understanding
- Technological complexity and technical limitations
- User experience and plausible loss of human interaction
- Changing survey landscape and comparability
- Ethical considerations
- Transparency and explainability

Responsible AI: Concerns to be addressed for benefits & risks, evaluated and continuously monitored

Concerns of survey methodologist vs potential use of AI II

Plausible concerns of survey methodologist vs potential use of AI

Slide II

Surveys tend to be by nature conservative to be trusted for maintaining high quality. Concerns relate to:

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- Technological complexity and technical limitations
- User experience and ~~plausible loss of human interaction~~
- Changing survey landscape and comparability across statistical areas and time
  Ethical considerations
- Transparency and explainability

Responsible AI: Concerns to be addressed for benefits & risks, evaluated and continuously monitored.

Restricting use of AI into improving the production process, *excluding AI-generative content*, we can respond to few concerns at the initial phase.

Response authencity is always a concern, and also respondents may choose to use AI for answering

Concerns of survey methodologist vs potential use of AI III

Plausible concerns of survey methodologist vs potential use of AI

Slide III

Surveys tend to be by nature conservative to be trusted formaintaining high quality. Concerns should be addressed and both benefits and risks evaluated and continuously monitored. Concerns relate to:

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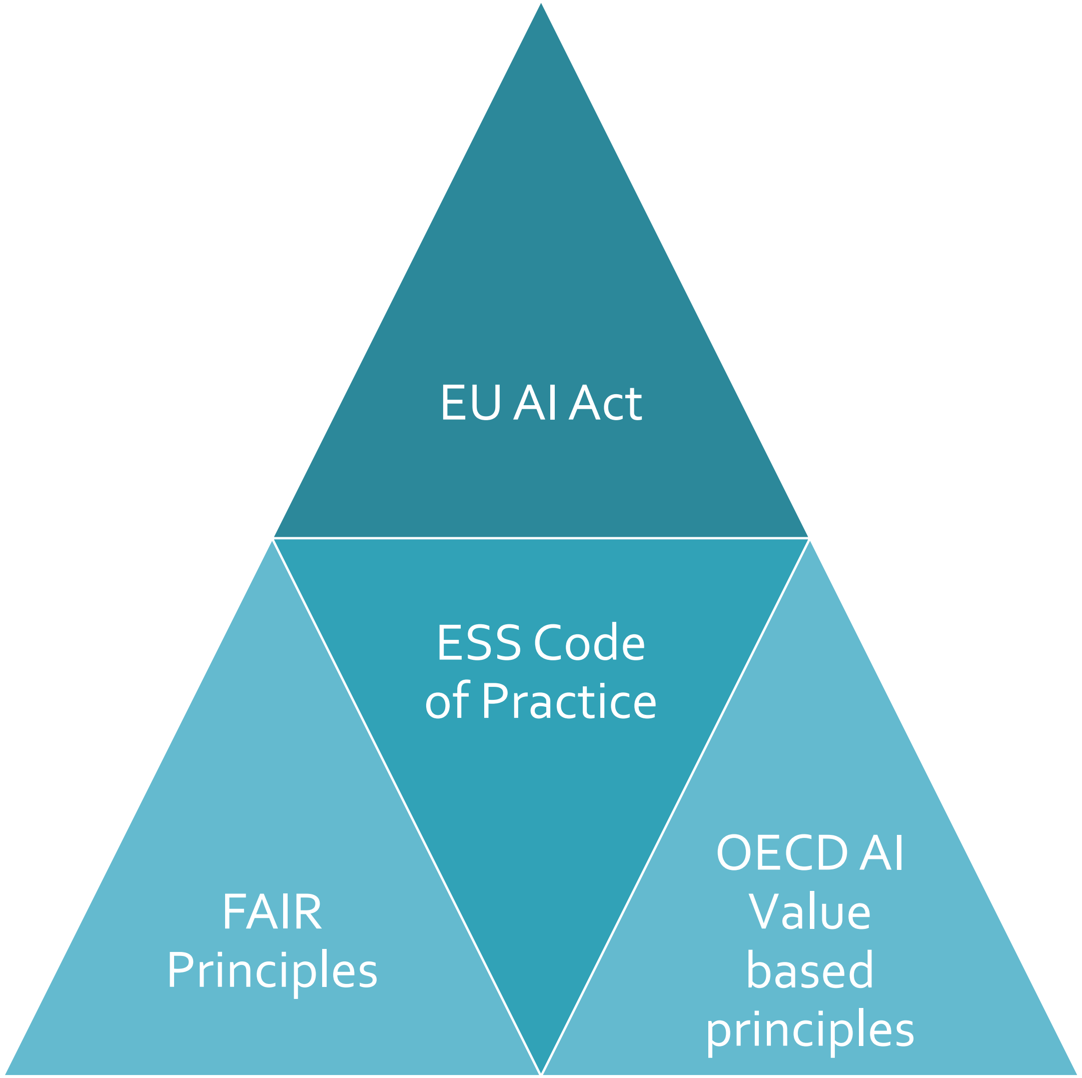
- Changing survey landscape and comparability across statistical areas and time
- Ethical considerations
- Transparency and explainability

Responsible AI: Concerns to be addressed for benefits & risks, evaluated and continuously monitored.

Following the EU AI and Data Act as well as the FAIR principles of AI we can ensure that the highlighted concerns are dealt in responsible manner in the process.

Remaining concerns are in areas where use of AI in can bring improvements to the current pain points.

Acceptability of using of machine learning in relation to Code of practise, AI Act and FAIR principles and other frameworks



How ESS quality criteria of statistics link with principles of responsible AI in surveys

EU AI Act
Legal framework for implementing AI within EU

ESS Code of practise
General Quality of statistics, processes & organization

Responsible AI in surveys

FAIR principles
Scientific data management and stewardship for openness and transparency

AI Value based principles / OECD
Promotion of AI that is innovative, trustworthy, respecting human rights & democratic values

FAIR and responsible AI for building trust can be used also for Official Statistics

GO FAIR

F INDABLE

Data includes unique identifiers and rich metadata to enable automatic discovery

A CCESSIBLE

Using the assigned identifier, data can be accessed by humans and machines. Open access protocols are clearly defined

I INTEROPERABLE

Using common vocabulary and formatting, data can be integrated with other workflows for analysis, storage & processing

R EUSABLE

Data includes clear usage licenses and detailed provenance. Metadata and data meet domain relevant community standards

Source: Jacobsen et al. 2019 with ref to Wilkinson et al. 2016 for scientific data management and stewardship

Specific objectives of the EU AI Act aim for legimate, trusted and responsible use of AI

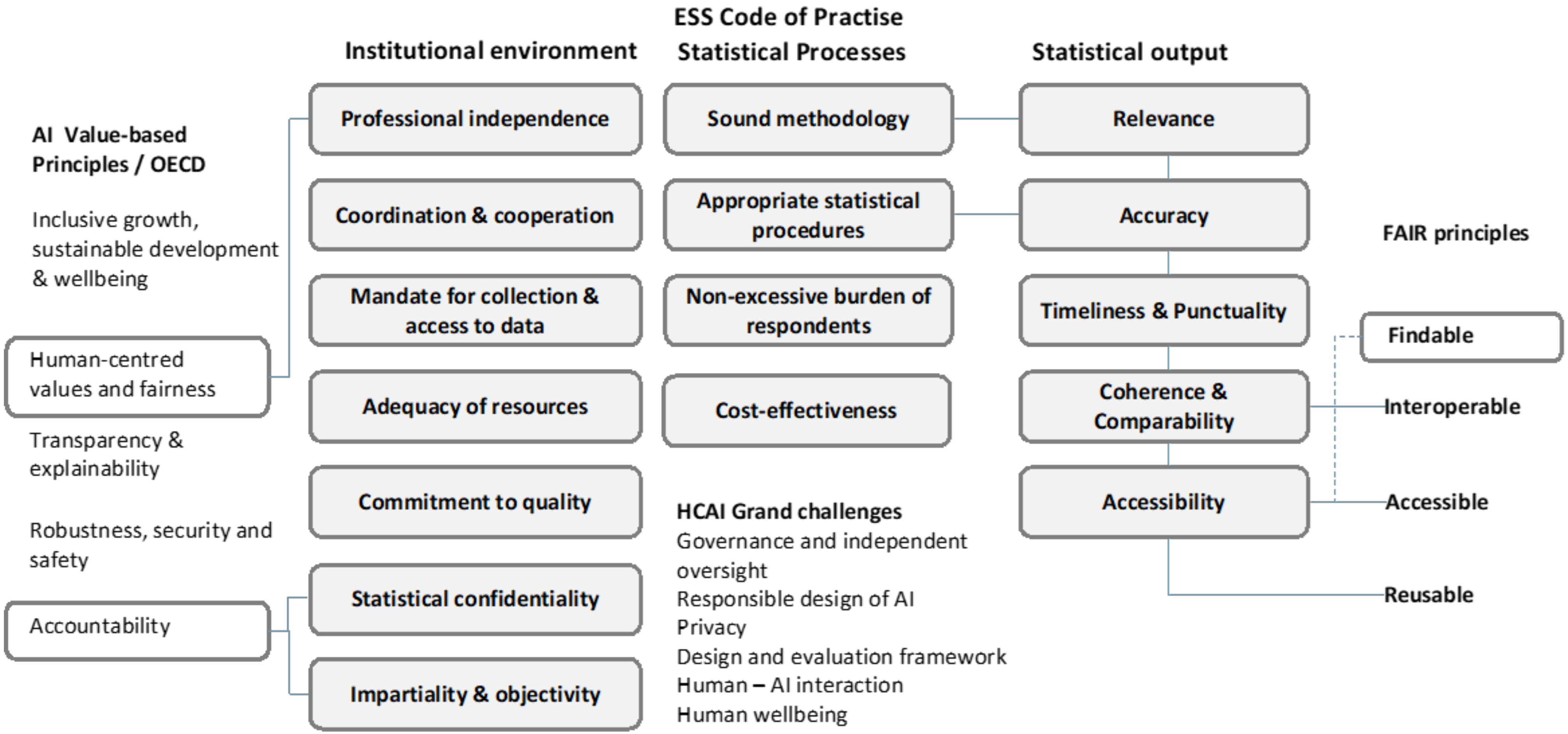
- AI systems are safe and respect existing law on fundamental rights and Union values
- **Legal certainty** to facilitate investment and innovation in AI
- Enhance governance and effective enforcement of existing law on fundamental rights and safety requirements applicable to AI systems
- Facilitate the development of a single market for lawful, safe and trustworthy AI applications and prevent market fragmentation.

The EU AI Act - Measures in support of innovation

- Legal framework to be innovation-friendly, future-proof and resilient to disruption.
- National competent authorities encouraged to set up regulatory sandboxes and sets a basic framework in terms of governance, supervision and liability.
- AI regulatory sandboxes for controlled environment to test innovative technologies for a limited time based on a testing plan agreed with the competent authorities.

→ Objective of AI act is not only about improving reach savings but also to improve the service for citizens, businesses, society and environment

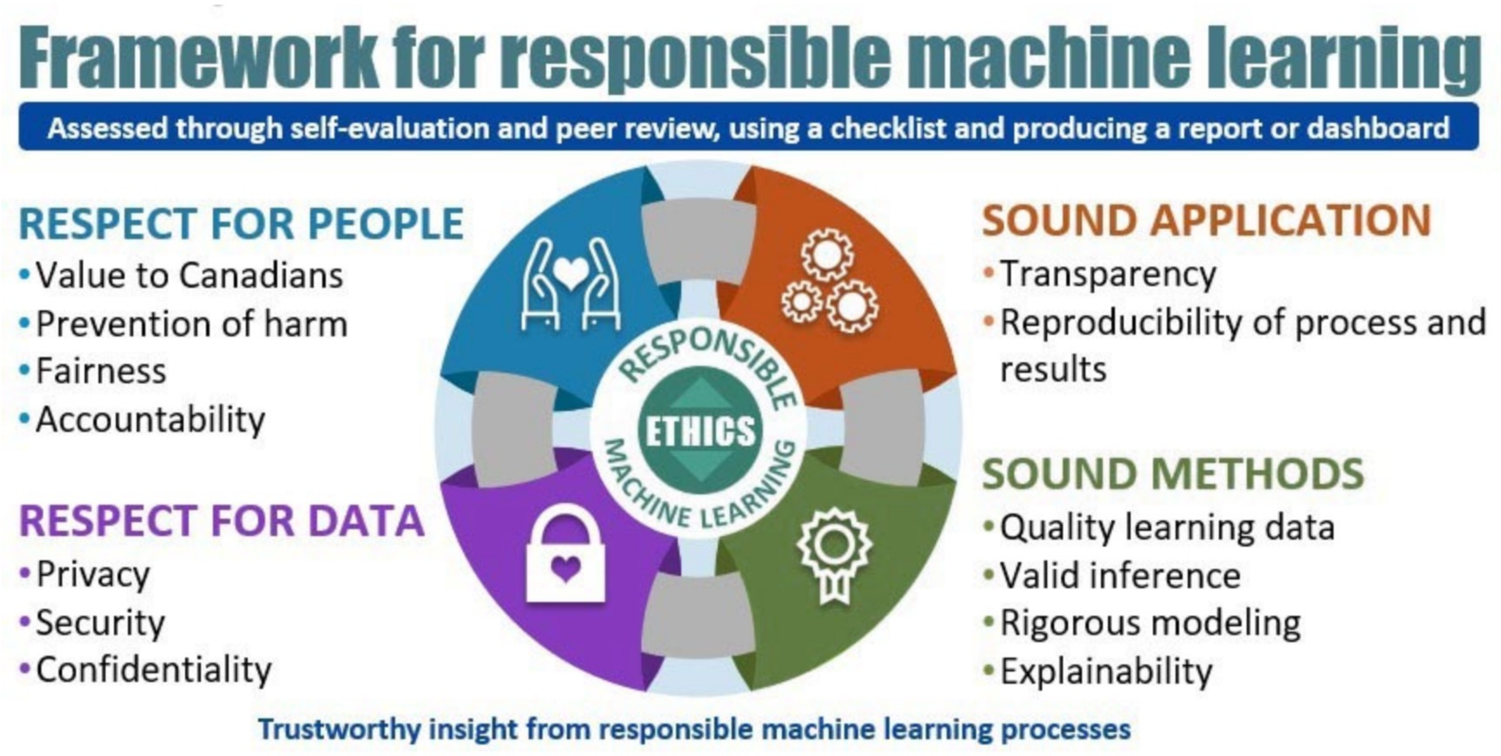
How ESS quality criteria of statistics link with principles of responsible AI



Ethical AI governance framework (based on EU AI Act)

Source: OECD AI Observatory

Transparency and trust for use of ML methods is gained via principles and frameworks – Case Statistics Canada



Source: Bosa K. (2023) Responsible use of machine learning at Statistics Canada

Directive on automated decision making:

"The objective of the Directive is to ensure that Automated Decision Systems are deployed in a manner that reduces risks to Canadians and federal institutions, and leads to more efficient, accurate, consistent, and interpretable decisions made pursuant to Canadian law."

VI. How to build and maintain trust when using AI and ML

How to build and maintain trust when using AI and ML

- Transparency on the use of AI and machine learning
- Methodology reports and monitoring their approachability
- Do you measure use of statistics – What about the usage of Quality and methodology reports? To whom are they written?
- AI policies on open, limited or close access models
- Acceptance of using training data
- Guidance on sharing data
- Ensuring unbiasedness, reproducibility and integrability
- Open evaluation of AI algorithms, similar to reporting quality of statistics and other methodologies

Open AI advancing AI governance: Voluntary AI commitments

Safety

- Commit to internal and external red-teaming of models or systems
- Work toward information sharing

Security

- Invest in cybersecurity and insider threat safeguards
- Incent third-party discovery and reporting of issues and vulnerabilities

Trust

- Develop and deploy mechanisms to understand if audio or visual content is AI-generated
- Publicly report model or system capabilities, limitations, and domains incl. fairness and bias
- Prioritize research on societal risks posed by AI systems
- Develop and deploy frontier AI systems to help address society’s greatest challenges

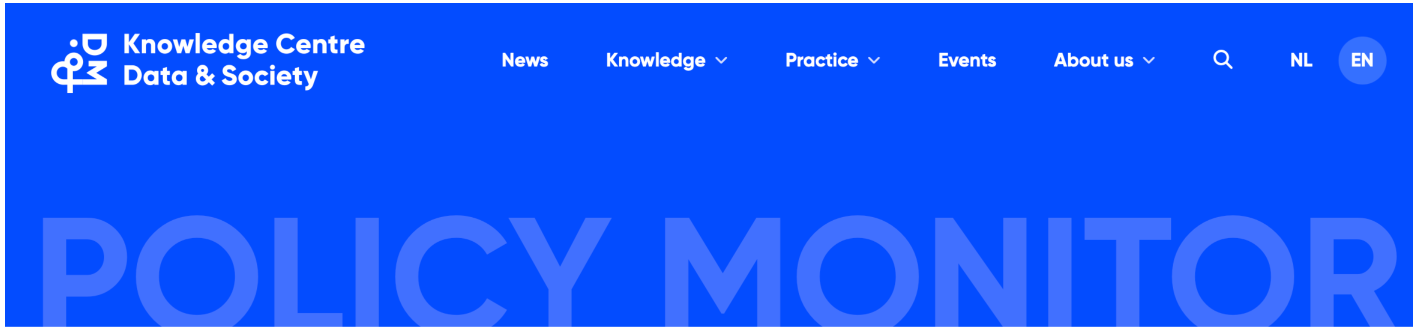
Source: https://openai.com/index/moving-ai-governance-forward/

Example on how to report on use of AI Case Urban development - City of Helsinki AI Register

- AI Register is a window into AI systems used by the City of Helsinki.
- Through the register, you can get acquainted with the quick overviews of the city's AI systems or examine their more detailed.
- Register gives information e.g., on data sets, data processing, non-discrimination, human oversight, and risk management and contact details to the team responsible.
- You can also give feedback & participate in building human-centered AI in Helsinki.

Example on how to report on use of AI Case Urban development - City of Helsinki AI Register

- The Dutch government published a public algorithm register on 21 December 2022.
- The register was announced in the Dutch government's coalition agreement
- The government wants algorithms used by the government to be legally checked for discrimination and arbitrariness.
- The register ensure transparency and should make an important contribution to making the application and outcome of algorithms more explainable.
- The Netherlands hereby follows the example of the cities of Amsterdam and Helsinki, which already have algorithm registries at the city level.



Netherlands – The Dutch government's Algorithm Register

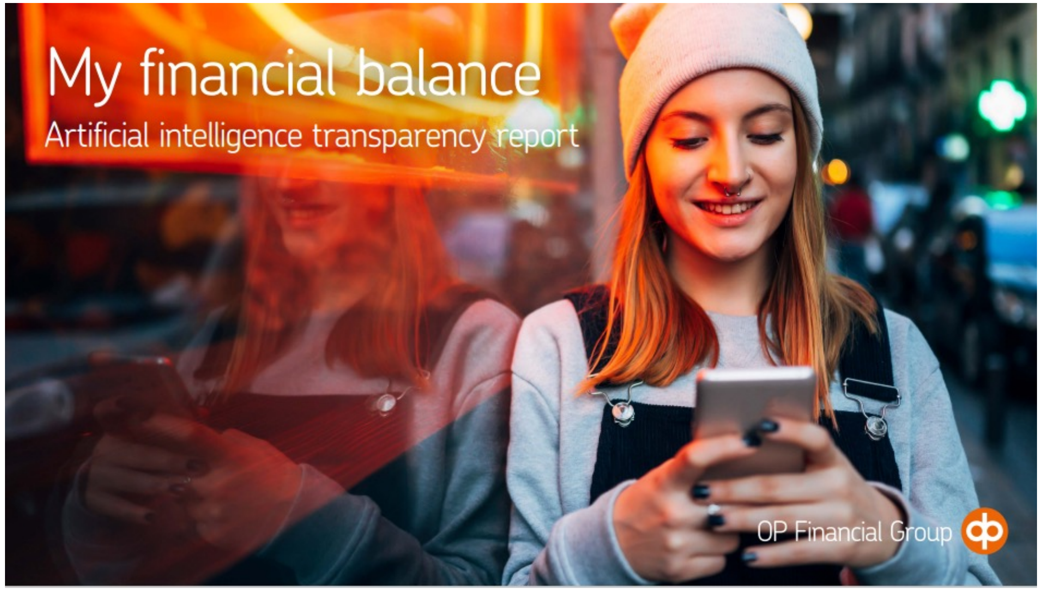
Example on how to define AI ethics & recogn impact - AI Registry of Scotland

In 2021 the Scottish AI Alliance published Scotland's AI Strategy & the high level Principles for AI in Scotland:

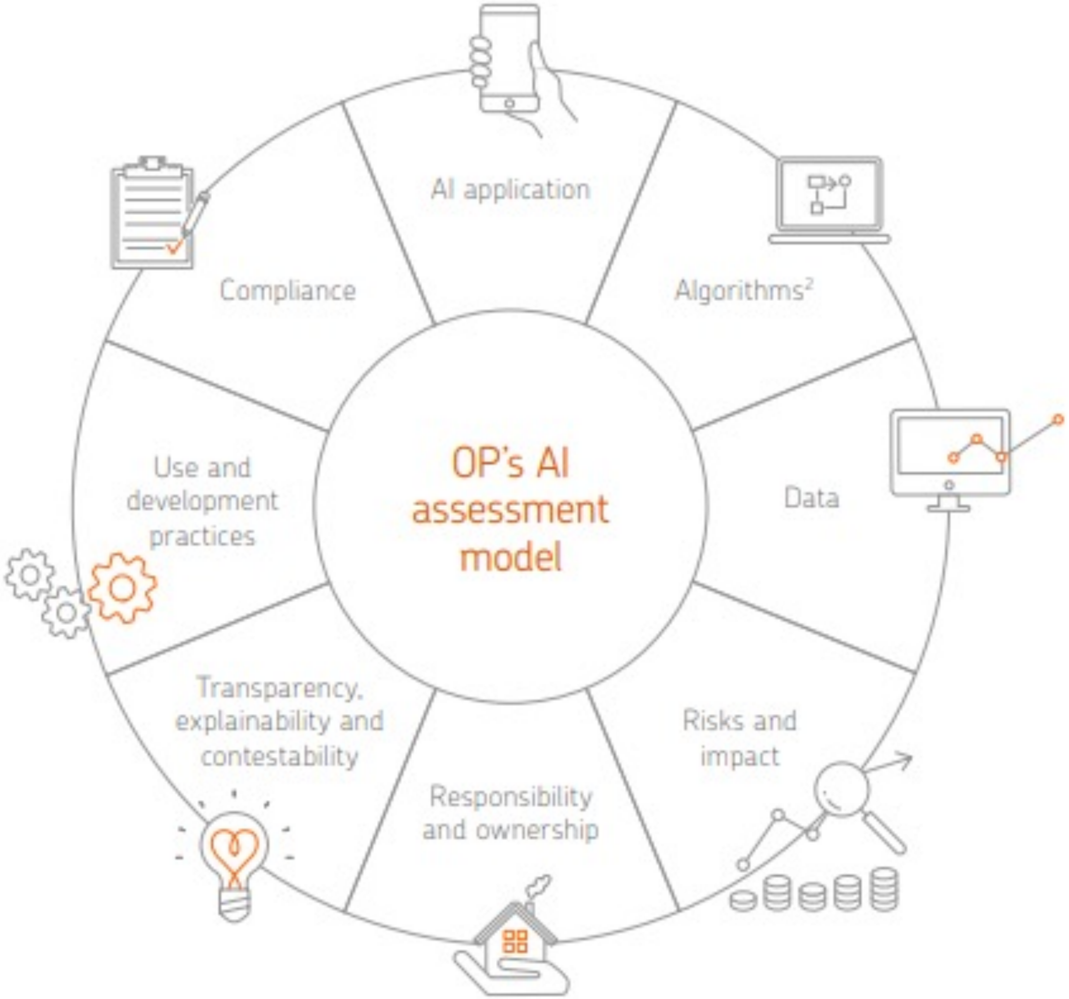
- AI should benefit people and the planet.
- AI systems should respect the rule of law, human rights, democratic values, and diversity.
- There should be transparency and responsible disclosure around AI systems.
- AI systems must be robust, secure, and safe.
- Organisations and individuals developing, deploying, or operating AI systems should be held accountable for their proper functioning.

"We also adopt UNICEF's policy guidance on AI for children when working with AI systems that impact children.
These ethical guidelines are key to how we want AI to work in Scotland."

Example on how to report on use of AI Case OP Finance Group: Artificial intelligence transparency report



Banks are generally regarded as trustworthy users of AI and data, largely due to regulations and auditing requirements.

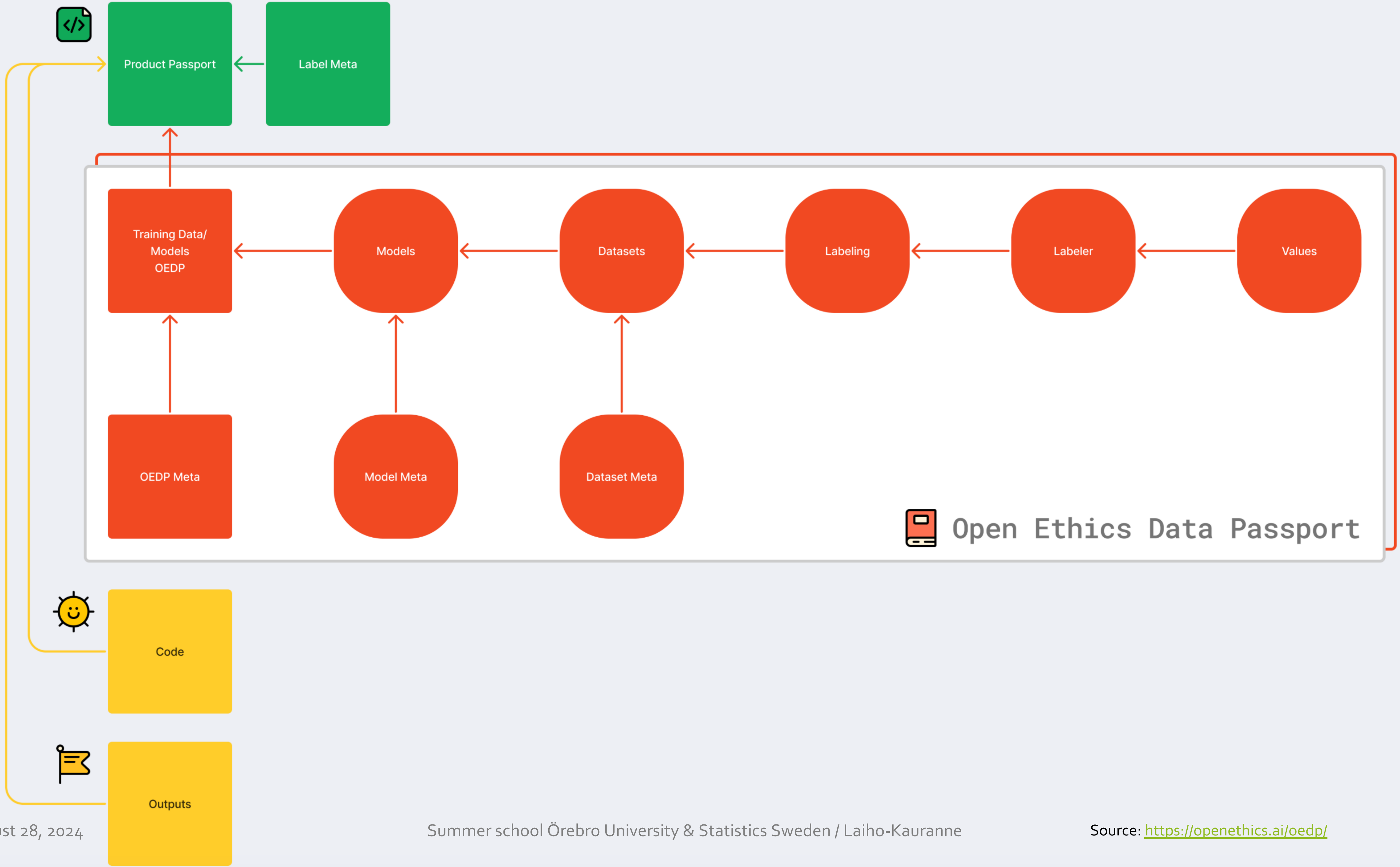


Source: OP Finance Group
Artificial intelligence transparency report

References on AI / Algorithm registers and Open Ethics Data Passport

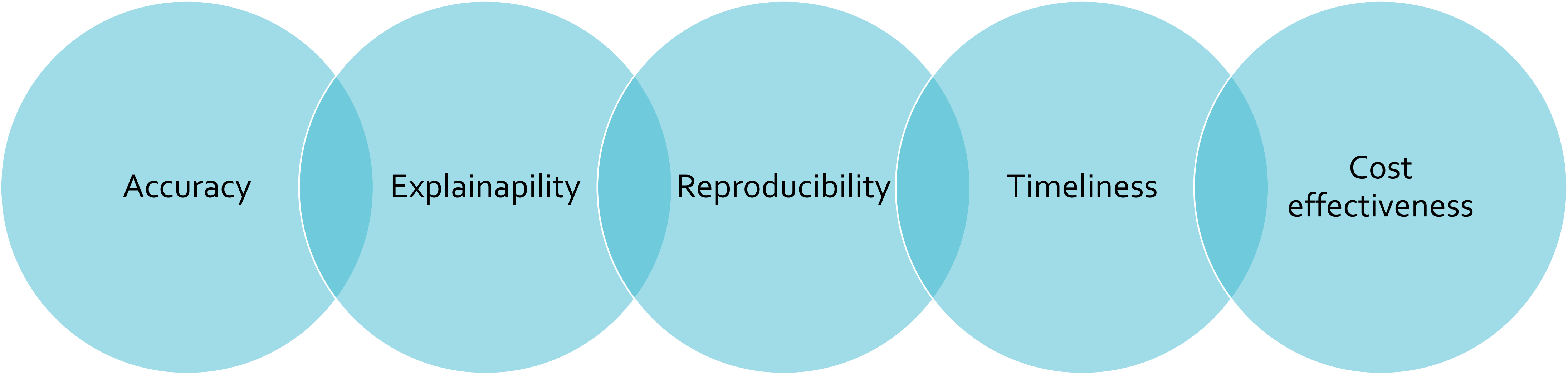
- Open AI – Moving AI Governance forward - link
- City of Helsinki AI Register - link
- Scottish AI register - link
- Netherlands – The Ducth Government algorithm register - link
- City of Amsterdam Algorithm register - link

- Open Ethics Data Passport (OEDP) - link



Source: https://openethics.ai/oedp/

Quality framework for statistical algorithms QF4SA dimensions:



Source: UNECE (2021) Machine learning for Official Statistics

New tools but how to utilize AI in responsible manner

Towards an Ethics of Artificial Intelligence

- The world must ensure that new technologies, especially those based on AI, are used for the good of our societies and their sustainable development.
- It should regulate AI developments and applications so that they conform to the fundamental rights that frame our democratic horizon.

Source: UNESCO 2018, Azoulay A. December 2018, Nos. 3 & 4 Vol. LV, "New Technologies: Where To?"

How best to unlock potential and scalability of AI & ML solutions

- Document the data & models; share the POC & MVP & data catalogues amongst interest parties
- Transform production processes into services to all stakeholders including data providers
- Organizations typically already have internal or external skills for managing data, data warehouses, and report development.
- Managing greater volumes of data and advanced analytics requires new skills.
- Holistics development requires open comparison of methodologies across subject areas

Commonalities of well managed of AI & ML solutions

- Well defined use cases identifying the pain points including risk assessments and ethical concerns – both from user and producers perspective
- Linked to data strategy & vision driven with clear measurable KPIs
- Solutions are related to agreed statistical program or roadmap for POC – MVP – Data product
- Development is built upon wider cooperation between data user, data teams and users
- Productization is supported by data architecture and clear ownership
- Solutions are kept alive with updating procedures for data and training the model

What do the organizations require to succeed in use of AI and ML

General requirements:

- Vision & data strategy
- Data governance and risk management
- Clear roles and responsibilities
- Clarifying ownership of data
- Human skills
- Commitment to continuous development
- Culture and incentives leading to innovations

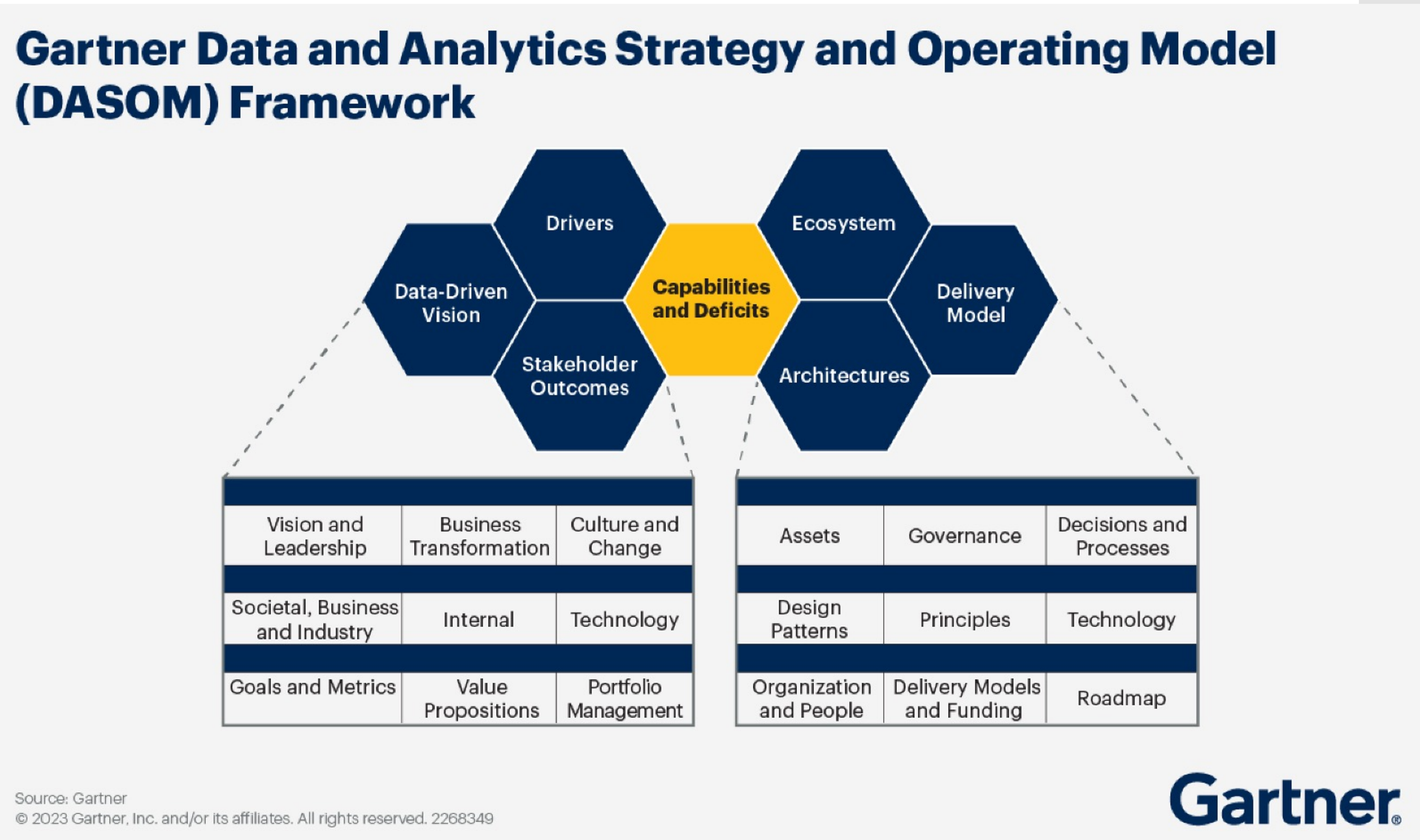
How do the public and private organizations respond?

Source: Finansförbundet, 2023:

- 35% of Nordic organisations are recruiting staff with digital skills, including the ability to assess when and how best to use AI.
- High demand for 'digital integrators', i.e. employees capable of applying digital technologies to new products and business concepts, but who do not design, develop or maintain digital solutions.
- Organisations primarily address needs via internal training and courses run by private providers, such as consultants.

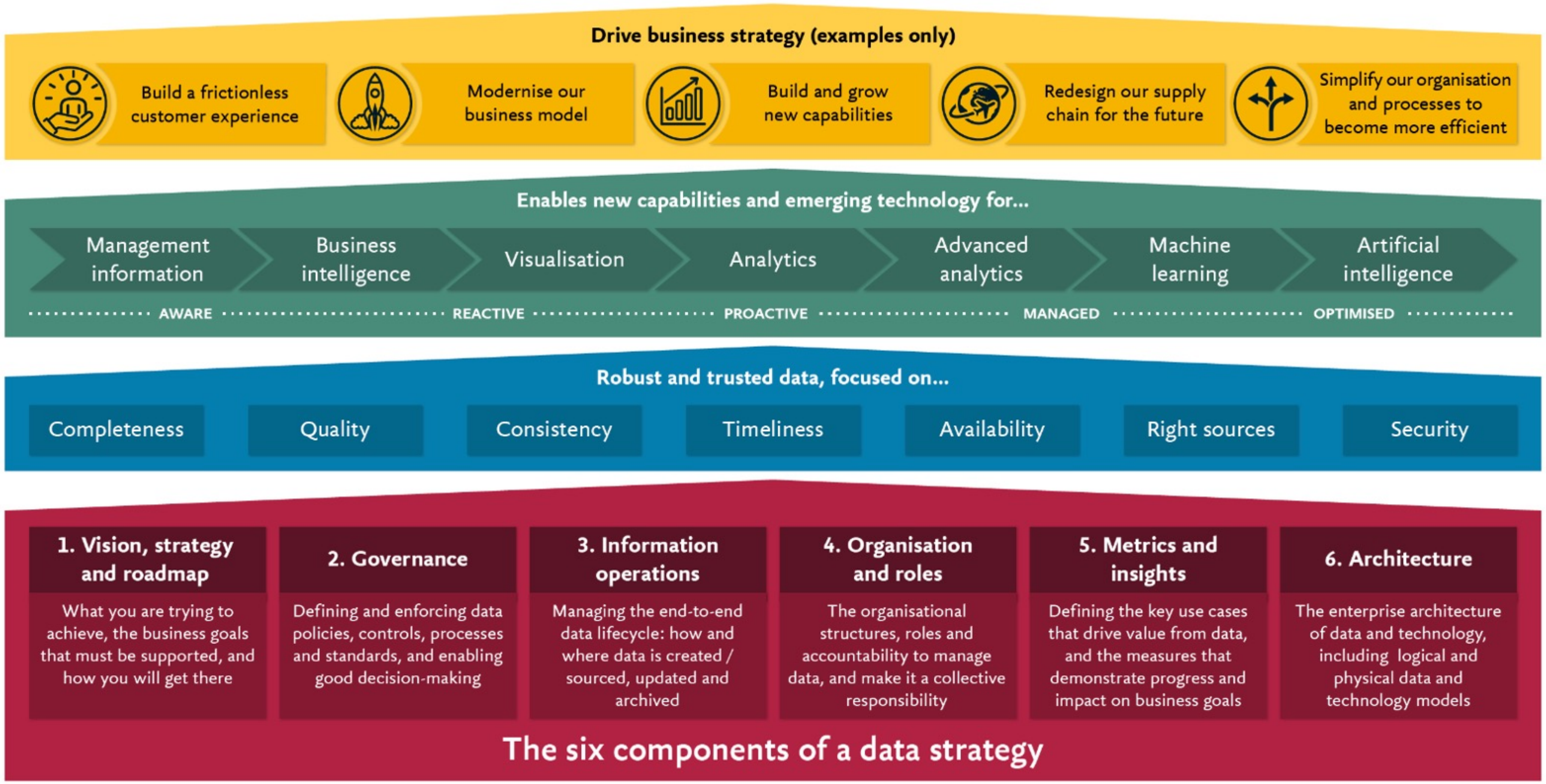
VII. Developing data strategy for ML & AI implementation

Alternative frameworks for building a data stragety for an organization: **Gartner**



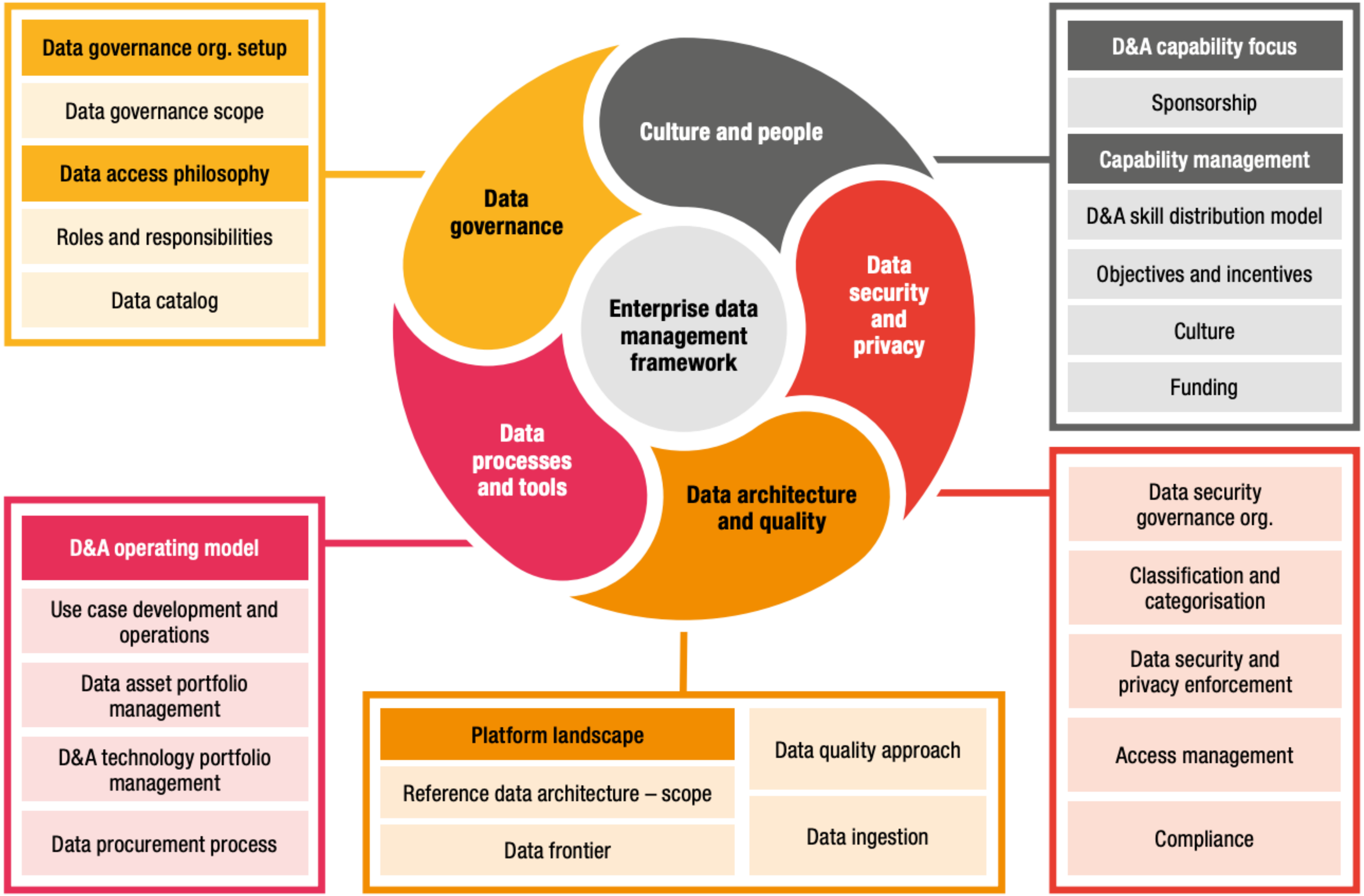
https://www.gartner.com/en/data-analytics/topics/data-analytics-strategy

Alternative frameworks for building a data stragety for an organization: **Berkley**



https://www.berkeleypartnership.com/news-and-insights/insights/the-six-components-of-a-data-strategy

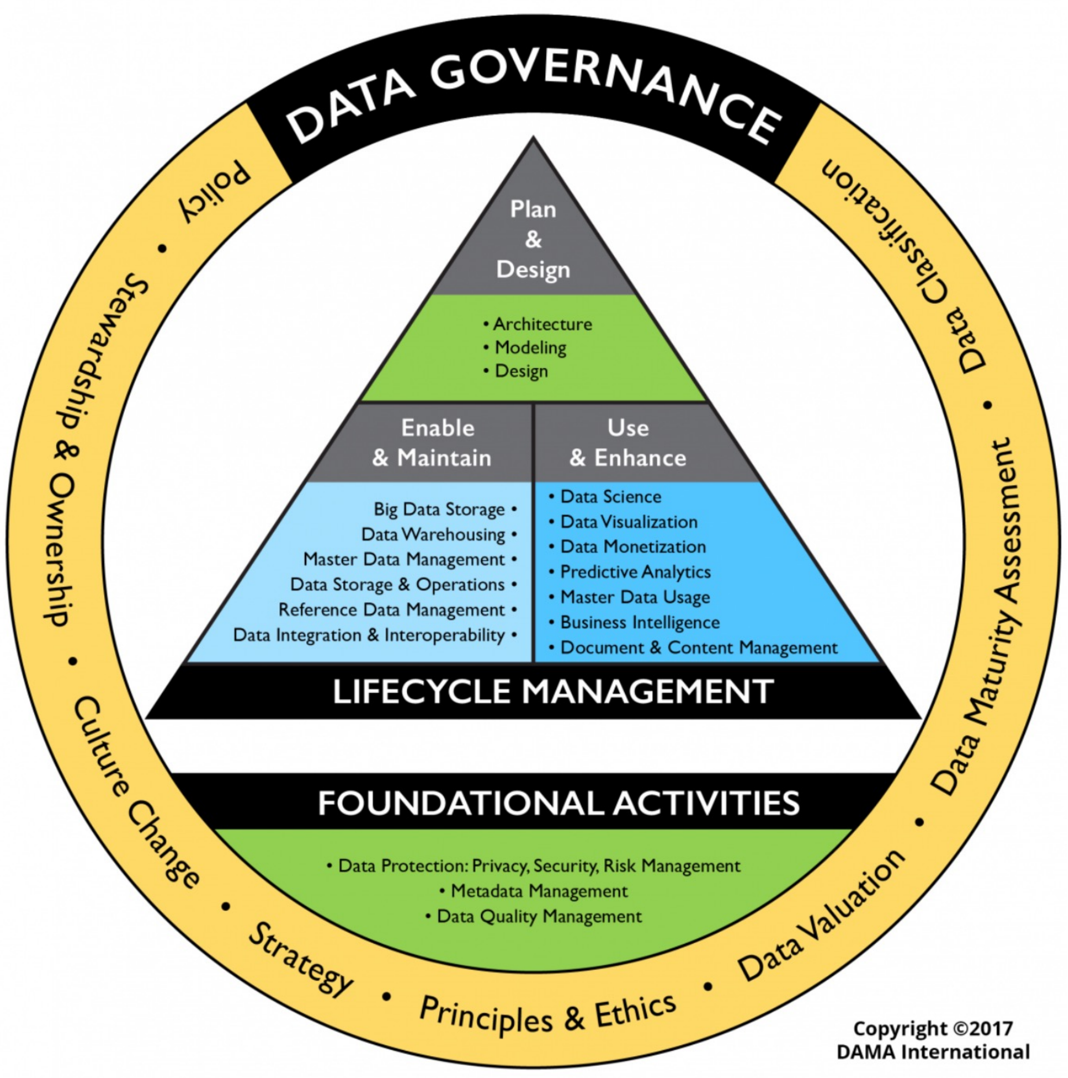
Alternative frameworks for building a data stragety for an organization: **PWC**



https://www.pwc.de/de/digitale-transformation/one-data-strategy-to-rule-them-all-pwc.pdf

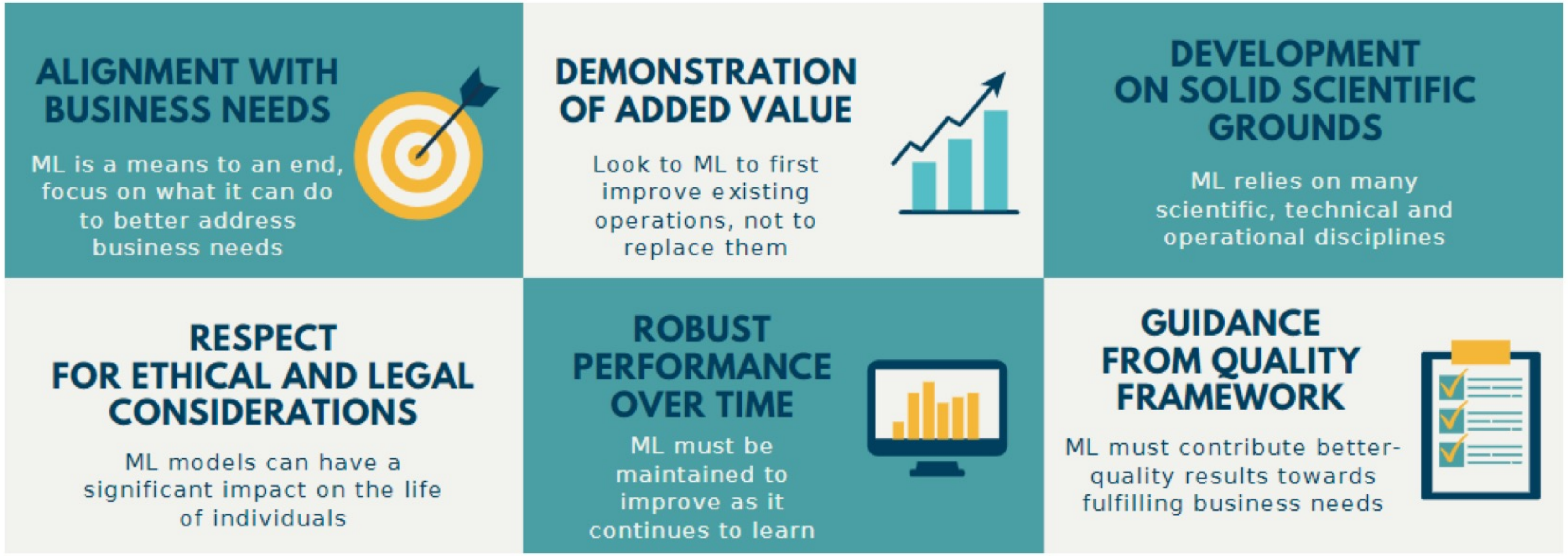
DAMA-DMBoK

gives foundation for data governance across organisation and provides also certification schemes



Source: https://www.dama.org/cpages/dmbok-2-wheel-images

Keys to fascilitating machine learning by UNECE



Source: UNECE Machine learning for Official Statistics
https://unece.org/sites/default/files/2022-09/ECECESSTAT20216.pdf

Conclusion

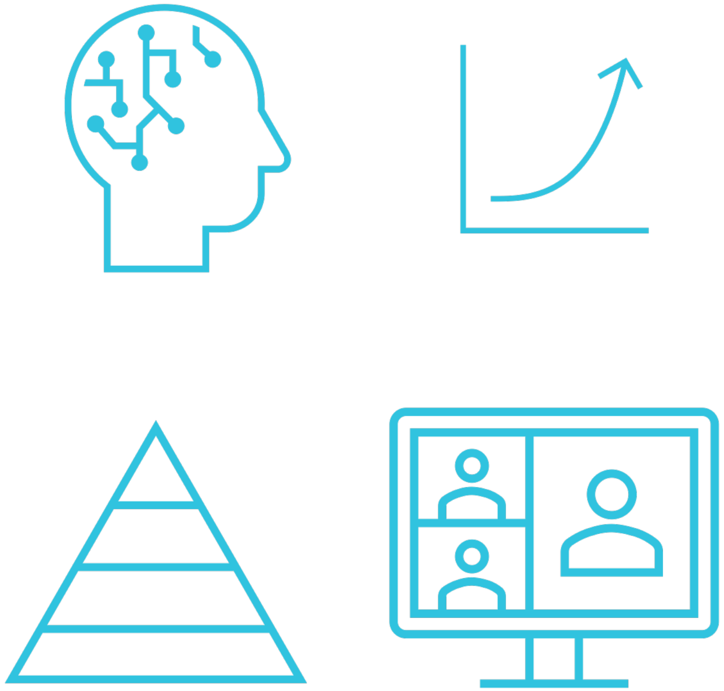
Key factors in success and acceptability of machine learning models in information production

1. Solid data governance
2. Getting the employees on board
3. Commitment to high quality
4. Professional ethics
5. Dialogue throughout statistics production process from data users, data providers and across production teams

Your thoughts:

Share your concerns in the Zoom chat on use of artificial intelligence and ML

- What are your thoughts and considerations regarding use of ML and AI?
- Are you working on a machine modelling development?
- Would you have a suggestion of a use case for statistical community to work on?



Thank you & Time for Q & A

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