# Data Quality Management Guidebook

## – Maximize the value of data and Artificial Intelligence –

**(Draft)**

2025-2-7

AISI Japan AI Safety Institute

IPA Information-technology Promotion Agency, Japan
Digital Infrastructure Center

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# Garbage in, Garbage out.

AI is amplifying existing data problems.
Quality of data directory impact on AI outputs.

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# ① Background

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- AI accelerates the change of our society. It provides useful and efficient services.
- But many people are concerned about the use of AI, and ensuring the accuracy of results is critical to making AI safe to use. To achieve this, it is necessary to improve the quality of data used for training and processing.
- AI society
  - AI systems rely on vast amounts of data for training and making results, that include predictions, recommendations and explanations.
  - The quality of data directly impacts AI system performance and effectiveness.
- Data driven society
  - High data quality is essential in a data-driven society because it ensures accurate and reliable information. It supports informed decision-making, reduces errors, and minimizes risks.
  - Quality data also improves customer satisfaction and helps organizations comply with regulations, protecting them from legal and financial issues.
- Ensuring data quality is essential to ensure reliability of AI services

# ② Data quality realizes trust in the society

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- Ensuring trust is crucial for the use of AI and data.
- Data is the foundation for AI. If that is not correct, the reliability of the entire process will be compromised.

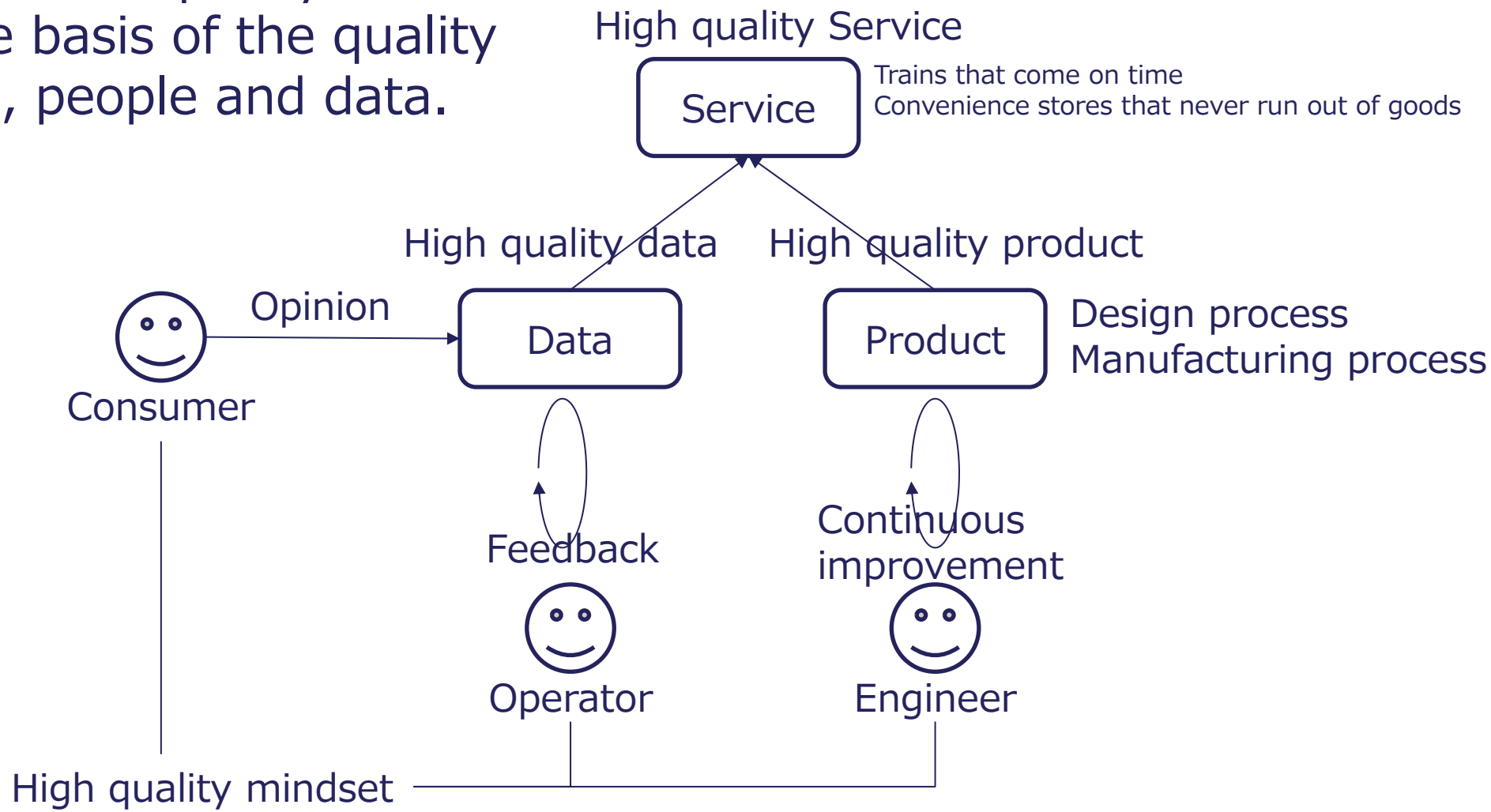
| Element of Trust in the data-driven society |
| --- |
| • Service quality |
| • Ethics |
| • Transparency |
| • Accountability |
| • Privacy protection |
| • Security |
| • Data quality |
| • Partnership and collaboration |

| Elements of Trustworthy AI |
| --- |
| • Accuracy and Reliability |
| • Ethics |
| • Transparency |
| • Accountability |
| • User-Centric Design |
| • Safety |
| • Continuous Improvement |

- Data quality is the foundation of AI excellence, enabling trustworthy AI that drives user adoption and engagement.

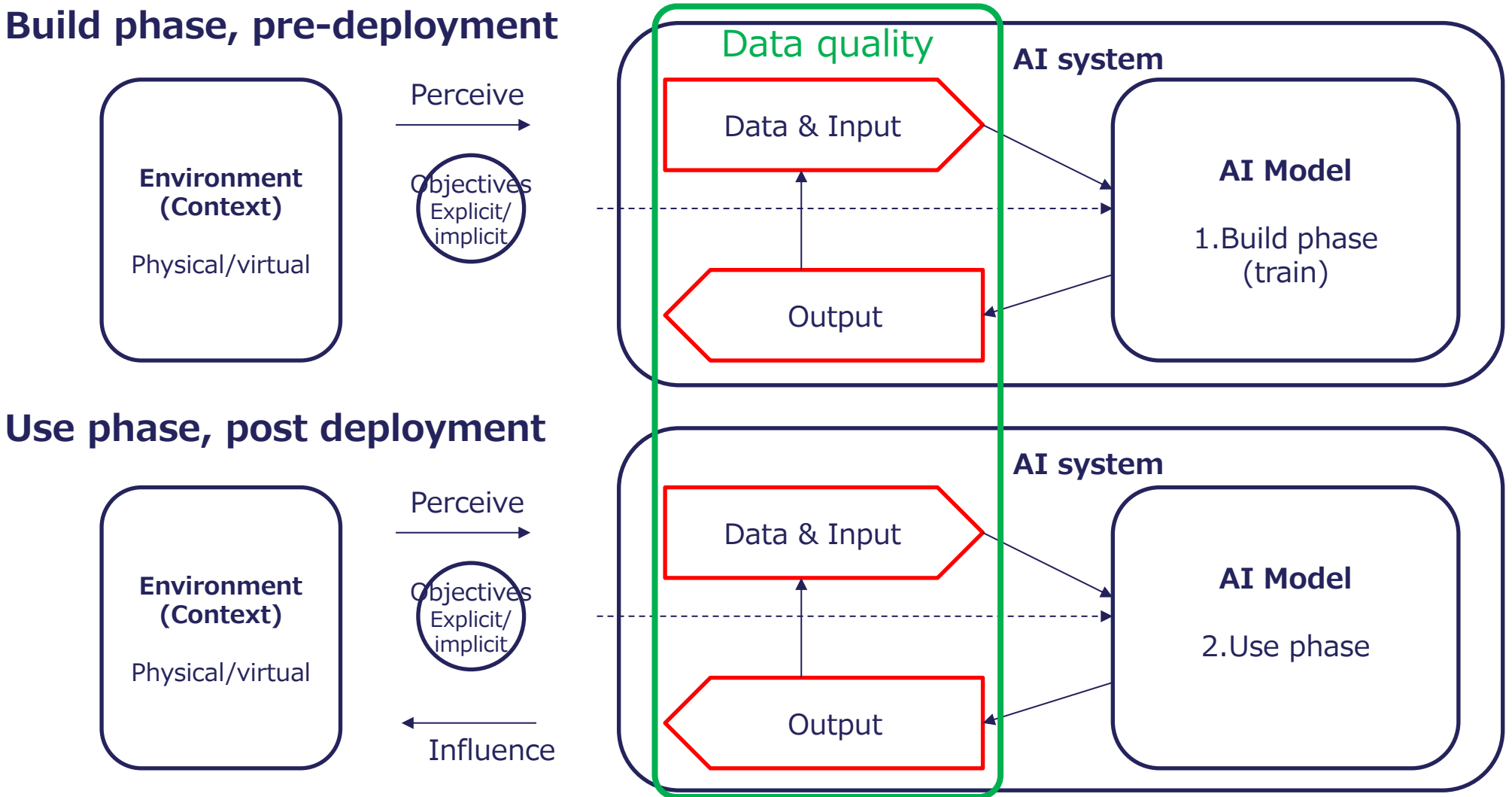
# Column: Service quality in Japan

Japan's high service quality is realised on the basis of the quality of its products, people and data.



# ③ AI system and Data quality

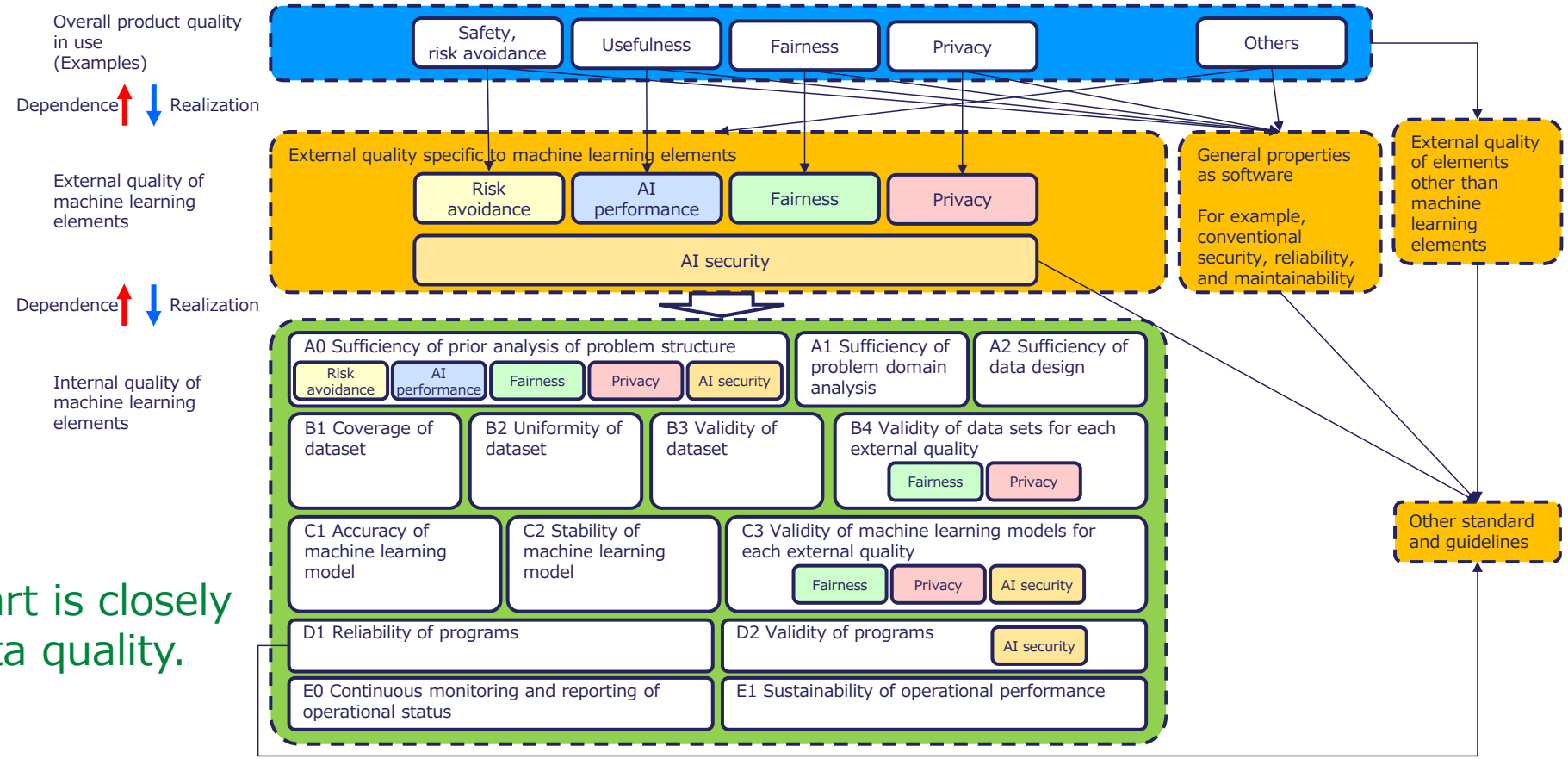
- In AI systems, data plays an important role not only at the time of use but also in the preparatory stage.




Updates to the OECD's definition of an AI system explained - OECD.AI

# Column: Data quality management in the AI system.

## Machine Learning Quality Management Guideline provide the following AI system structure. (See appendix)

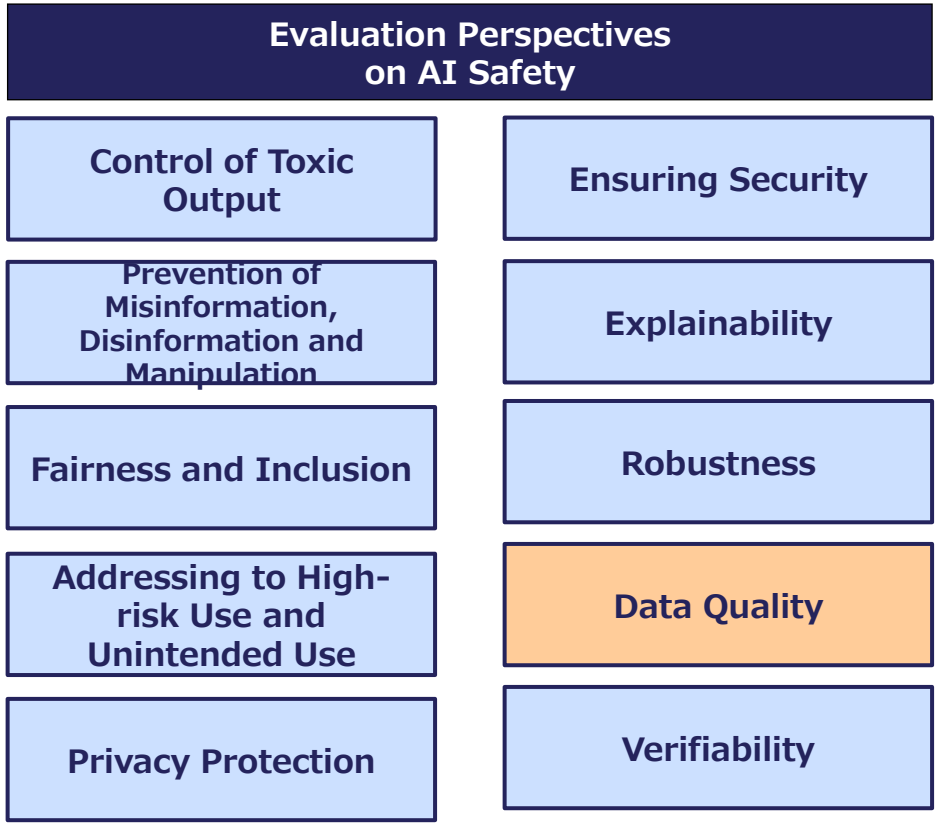



This green part is closely related to data quality.

# Column: Data quality is important for AI safety

**Guide to Evaluation Perspectives on AI Safety (2024-9-25, Japan AISI)**

- Low-quality input data affects a wide variety of matters, including the quality of AI models and the credibility, consistency and accuracy of AI output results. In turn, the credibility of society may be undermined.
- Data quality management is essential for the appropriate and safe use of AI.
- AISI's Guide to Evaluation Perspectives on AI Safety provides evaluation perspectives for building trustworthy AI and adds data quality as one of the ten.




https://aisi-go-jp.translate.goog/effort/effort_framework/guide_to_evaluation_perspective_on_ai_safety/?_x_tr_sl=auto&_x_tr_tl=en&_x_tr_hl=en-US

# ④ Benefit from Data Quality Management

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1. Enhanced Accuracy
   - Higher data quality results in more accurate and consistent AI predictions and decisions, reducing the risk of flawed outcomes.
2. Better Insights
   - Quality data enables the identification of actionable insights and reliable trends, empowering better decision-making processes.
3. Increased Efficiency
   - Clean, high-quality data reduces time spent on preprocessing tasks such as cleaning, correction, and normalization, allowing teams to focus on higher-value activities.
4. Improved User Experience
   - Accurate and relevant data enhances the overall experience for end-users by delivering precise, personalized, and timely results.
5. Reduced Errors
   - Minimizing inconsistencies and errors in data reduces inaccuracies in AI outputs, improving reliability and performance.
6. Cost Savings
   - Investing in high-quality data decreases costs related to error correction, reprocessing, and mitigating downstream issues caused by poor data quality.
7. Compliance and Security
   - Maintaining high-quality data ensures adherence to data governance, privacy regulations, and security standards, safeguarding organizational integrity.
8. Enhanced Trust
   - Consistently high-quality data builds trust in AI systems among stakeholders, fostering confidence in automated processes and decisions.
9. Scalability
   - High-quality data serves as a robust foundation for scaling AI systems, ensuring consistent performance as the system expands.
10. Facilitates Model Training and Updates
    - Clean and structured data simplifies the process of training and fine-tuning AI models, accelerating development cycles and improving model adaptability.
11. Competitive Advantage
    - Organizations leveraging high-quality data gain a significant competitive edge by delivering superior AI-driven products and services.
12. Ecosystem Integration
    - Reliable data quality enables seamless integration with other systems and platforms, ensuring interoperability and streamlined workflows.

# ⑤ Risk from Low–quality Data

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1. Decision-Making Errors
   - Inaccurate or incomplete data can lead to flawed analyses, resulting in incorrect conclusions, strategic missteps, and poor decision-making at all levels of the organization.
2. Operational Inefficiency
   - Time and resources must be allocated to cleaning and correcting low-quality data, delaying AI model deployment and reducing operational effectiveness.
3. Decreased Customer Satisfaction
   - Inaccurate or incomplete customer data can lead to poor personalization, unmet expectations, and diminished trust in services or products.
4. Increased Costs
   - Poor data quality increases costs through error correction, reprocessing, re-training of AI models, and potential financial losses due to incorrect predictions or recommendations.
5. Legal and Regulatory Risks
   - Non-compliance with data protection laws and regulations (e.g., GDPR, CCPA) can lead to hefty fines, lawsuits, and reputational damage.
6. Reputation Damage
   - Errors caused by poor data quality can damage trust and credibility with customers, partners, and stakeholders, potentially leading to long-term brand erosion.
7. Competitive Disadvantage
   - Competitors with better-quality data can outperform in key areas such as customer insights, operational efficiency, and market responsiveness, leaving organizations lagging behind.
8. Lost Opportunities
   - Missed insights and trends due to poor-quality data can result in failure to seize new market opportunities or innovate effectively.
9. Model Performance Degradation
   - AI models trained on low-quality data may exhibit biased, unreliable, or even harmful behavior, leading to ethical concerns and reduced effectiveness in real-world applications.
10. Security Risks
    - Poor-quality data may inadvertently include vulnerabilities or errors that malicious actors can exploit, leading to potential security breaches or misuse of sensitive information.
11. Stakeholder Distrust
    - Internal teams and external stakeholders may lose confidence in AI systems if the data quality consistently undermines reliability and results.

# ⑥ Cause of low-quality data

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- **Human error**: Mistakes made during data entry or data processing.
- **Lack of standardization**: Inconsistent formats and standards across data sources.
- **Inadequate data governance**: Absence of policies and procedures for data management.
- **Outdated systems**: Using legacy systems that are not equipped to handle modern data requirements.
- **Incomplete data collection**: Missing or incomplete data due to inadequate data collection processes.
- **Insufficient training**: Lack of proper training for personnel handling data.
- **Poor data integration**: Issues arising from merging data from different sources.
- **Limited quality control**: Inadequate checks and validation processes for data quality.
- **Unverified sources**: Using data from unreliable or unverified sources.
- **Bias in data collection**: Collecting data that reflects inherent biases.
- **Technical glitches**: Errors caused by software bugs or hardware failures.
- **Lack of documentation**: Inadequate documentation leading to misunderstandings or misinterpretations of data.
- **Misunderstandings**: Data entry errors due to misunderstanding the requirements or instructions.
- **Malicious actions**: Deliberate tampering or poisoning of data by someone with harmful intent.

# ⑦ Objective and Goal

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- Objective
  - Enhancing data quality for AI ensures that decisions, predictions, and recommendations are based on accurate, consistent, and reliable information. High-quality data empowers organizations to leverage AI effectively, reducing risks and unlocking its full potential. On a societal level, improving data quality fosters trust in AI systems, promotes ethical data use, and ensures equitable outcomes. It establishes a foundation for innovative applications in healthcare, education, and public services, ultimately contributing to economic growth and a better quality of life for all individuals.
- Goal
  - The goal of improving data quality is to create a robust ecosystem where accurate, secure, and accessible data enables AI to function at its best. This involves establishing standardized practices for data collection, cleaning, and validation. At the societal level, the aim is to democratize data-driven innovation, ensuring that all sectors benefit equally. By achieving this, we can promote transparency, enhance decision-making processes, and accelerate progress toward a sustainable and inclusive digital society where technology serves humanity responsibly and effectively.

# ⑧ Principle

- This guidebook is intended to help you use existing standards and accelerate their implementation, rather than create new ones.

Know your users and their needs.

Ensure it is fit for purpose.

Consider trade-offs between quality and cost.

Accept that errors will occur; don’t pursue perfection.

Review the design and consider the lifecycle.

Use mature services when there are existing common functions.

Get feedback from all stakeholders.

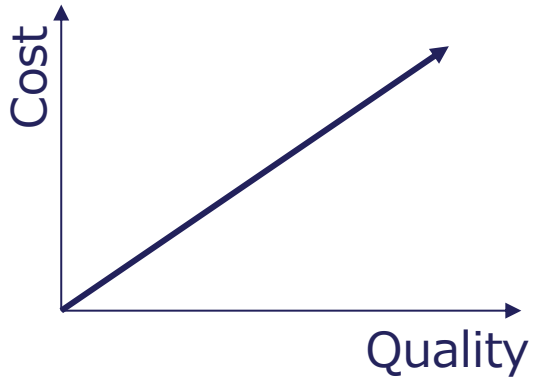
Visualize for easy confirmation and traceability


Balance of quality and cost

# Column: Quality and cost

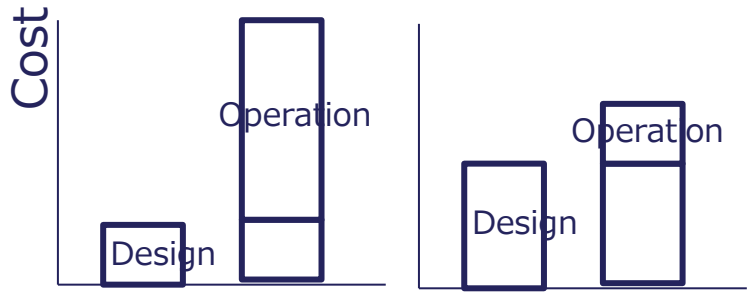
- When planning for quality, costs need to be considered

Quality and cost are proportional.



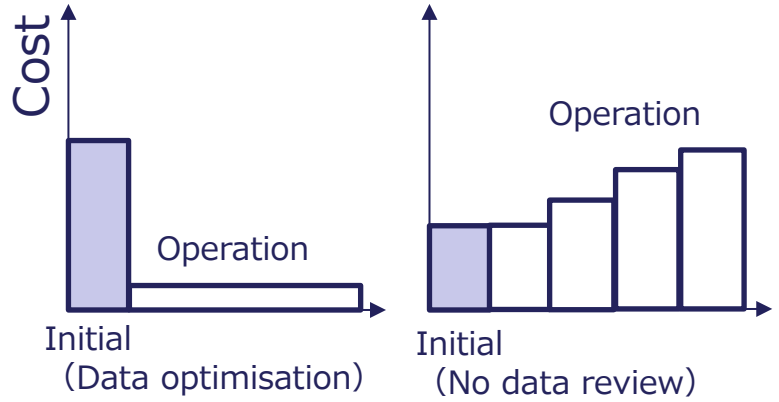

If you raise the quality above the target, it will cost more.

It is important to build quality in early processes such as design




If the design is appropriate, operating costs and total costs will decrease, and it will be possible to respond quickly to changes.

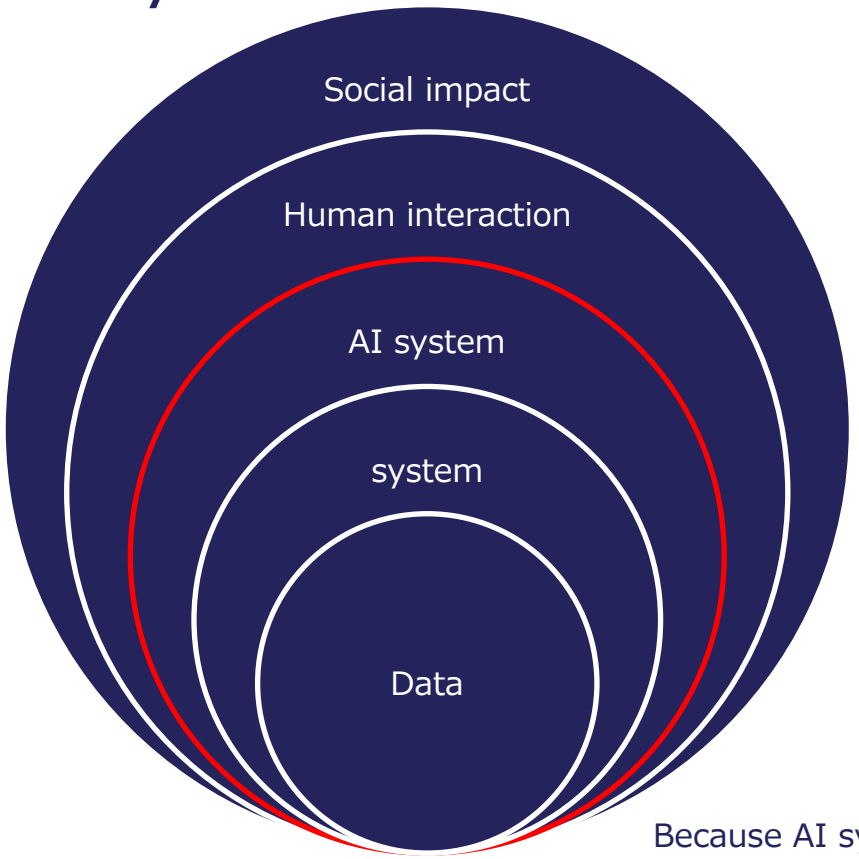
Consider not only transition costs but also operational costs




If you optimize your data when you implement the system, your operating costs will be lower.

# ⑨ Scope

- AI and data are important parts of society, but the scope is broad. They need to be considered in the context of the whole picture of society.

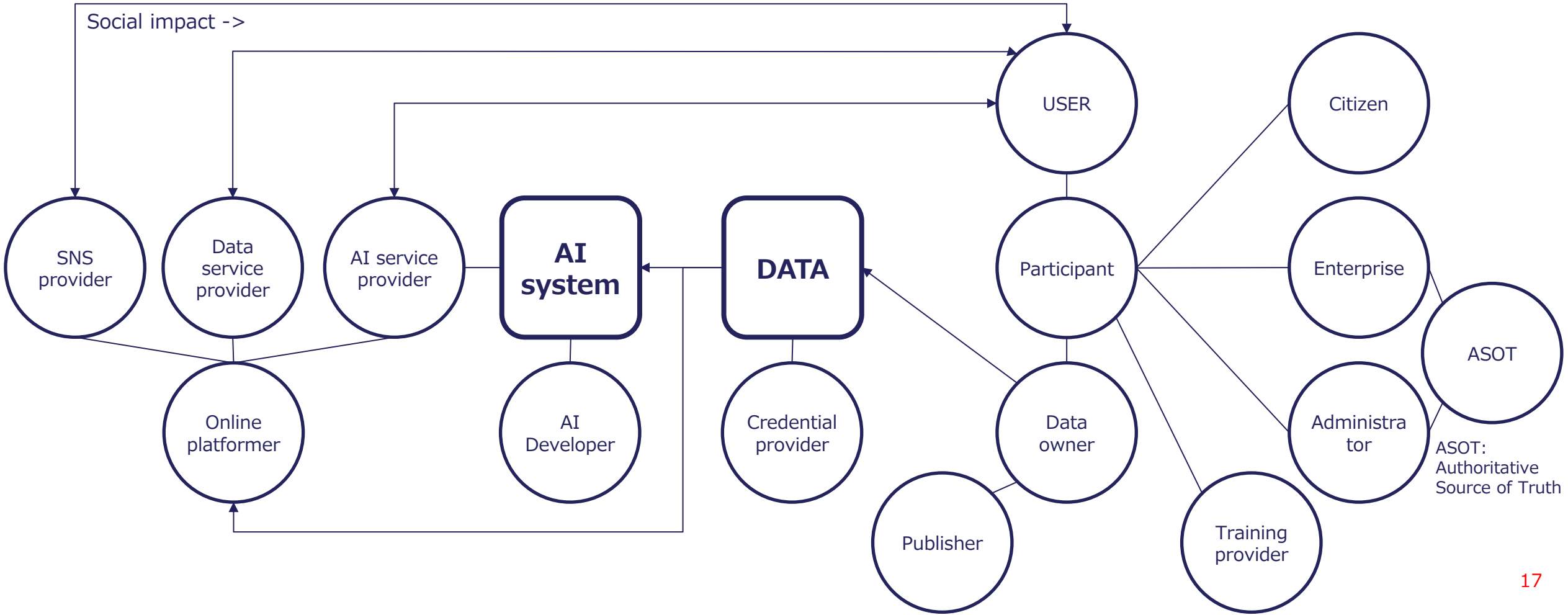



- Data type
  - Text
  - Numeric
  - Image
  - Video
  - Sound
- AI system
  - Narrow AI,
  - AGI(Artificial General Intelligence)

Because AI system includes training data, it can handle a wider range of data than traditional systems.

# ⑩ Stakeholders

- Stakeholders are diverse. They are characterized by the fact that everyone can be both a user of AI and a supplier of data.



# ⑪ Methods to ensure quality

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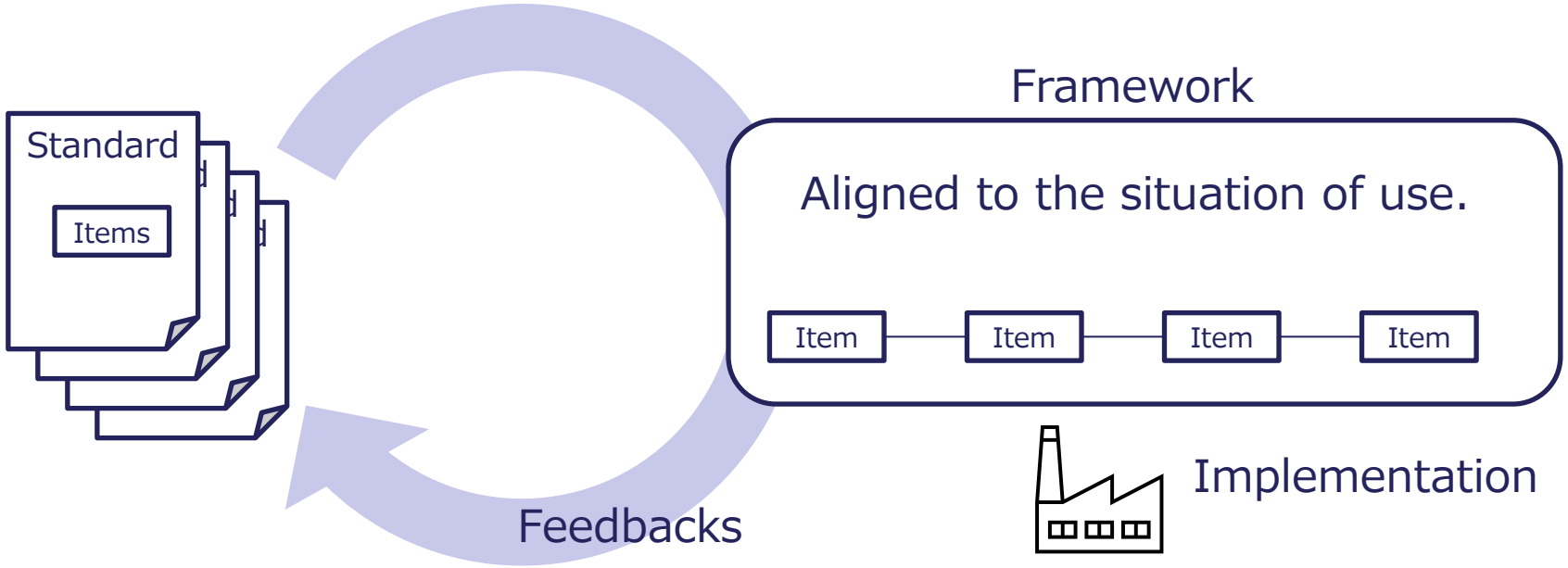
- The following methods are the main approaches to ensure data quality.

| Make high-quality data | Prevent low-quality data | Build trust | Use it right |
|---|---|---|---|
| • Sophisticated data design<br>  • Reference model<br>  • Data modeler<br>• No human intervention<br>• Validation at intermediate stages | • Validation(Input, Output)<br>  • Validator<br>  • Detector<br>  • Converter<br>  • Cleansing tool<br>• Human check | • Verification of Provenance<br>• Digital contents transparence technology(DCT)<br>  • Watermark | • Training<br>• UI/UX<br>• SSOT & ASOT<br>• Labeling |

| Governance |
|---|
| • DataOps(Update and feedback) |

# ⑫ Relation of ISO standards and framework

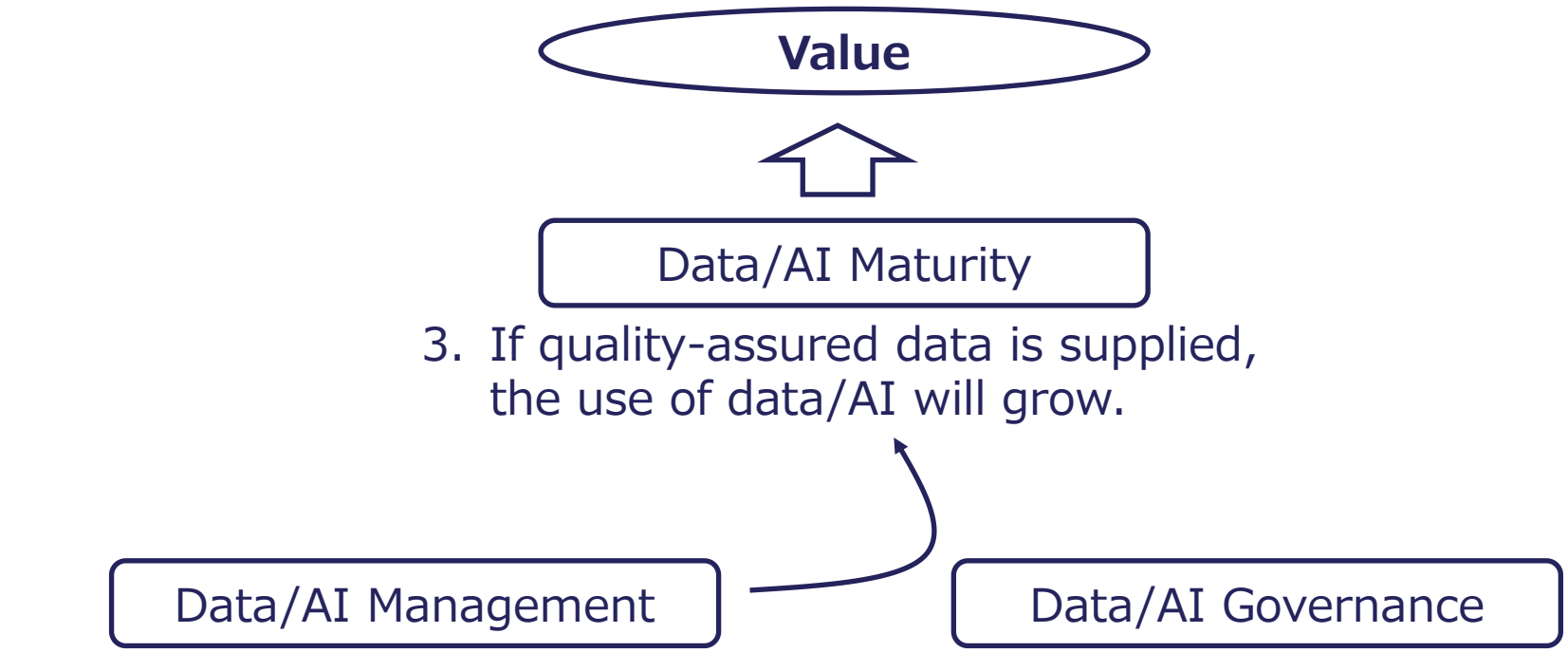
- The framework will organize and guide the many standards on data quality in a way that makes them easy to implement.
- It does not create new standards, but is only a practical guide, and synergies can be achieved by feeding the results of implementation back into the standardization effort.



# II. Concept of the data quality management framework

# ① Management, Governance and Maturity

- Continuing to provide good quality data is important to encourage widespread adoption of AI.



# ② Concept of Data quality framework

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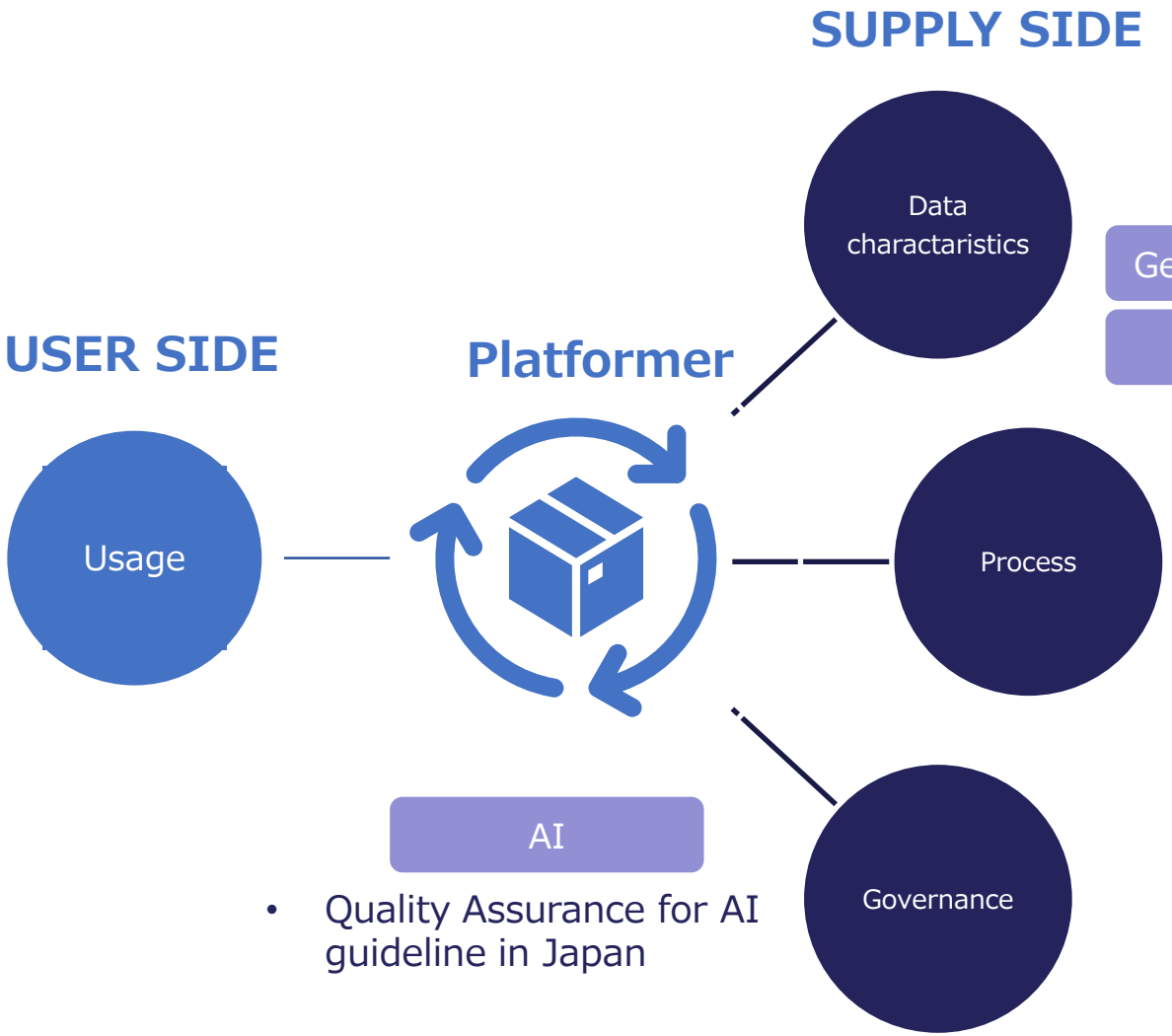
- Data connect to the world, so global interoperability is essential.




- Is the data of sufficient quality?
- ISO/IEC 25012
- ISO/IEC 5259

Geospatial data
- ISO 19157

IOT
- DSA whitepaper in Japan

- Are there any issues with the process?
- ISO/IEC25024
- ISO/IEC 8183
- ISO/IEC 5259-1

- Is the data being managed strategically?
- ISO 8000-61
- ISO/IEC 38505-1
- ISO/IEC 5259-5

# ③ Framework

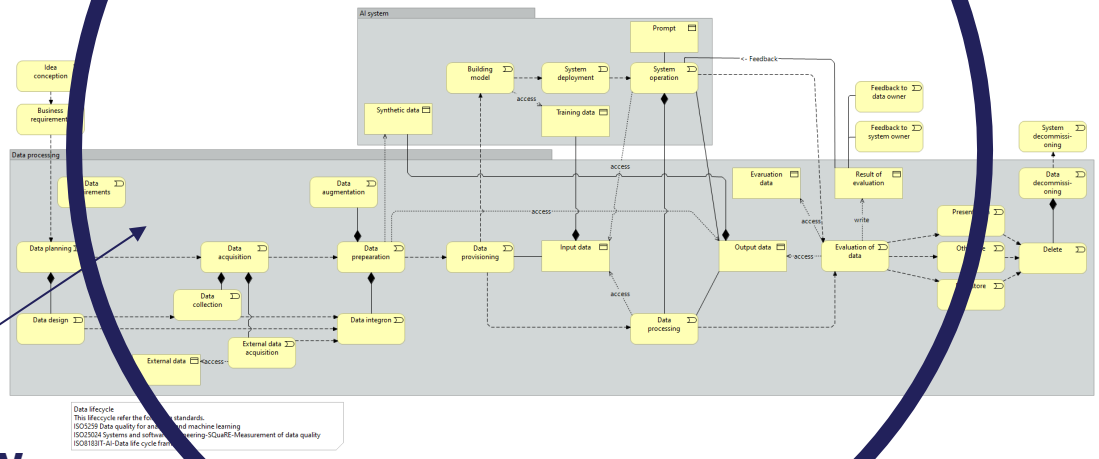
- This framework consist of 3 views. They cover both management and operations.

**Governance cycle view**

Ensure the organization has a sustainable structure.

**Process view**
(Operation)

Identify actions required at each stage.




**Gateway view**
(Characteristics)

Define check items.

# ④ Characteristics

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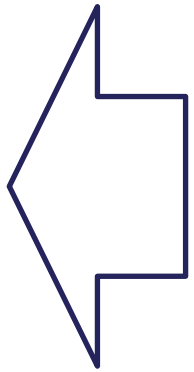
ISO/IEC 5259-2

**Problems**

Inaccurate data
Not formatted data
Out-of-date data
Data from unknown sources
Poisoned data
Spike data
Non calibrated data
Mis/Dis/Mal-information
Bias
Incomplete data
Duplicate data
Inconsistent data
Irrelevant data
Corrupted data
Ambiguous data



**Inherent data quality characteristics**

- Accuracy
- Completeness
- Consistency
- Credibility
- Currentness

**Inherent and system-dependent data quality characteristics**

- Accessibility
- Compliance
- Efficiency
- Precision
- Traceability
- Understandability

**System-dependent data quality**

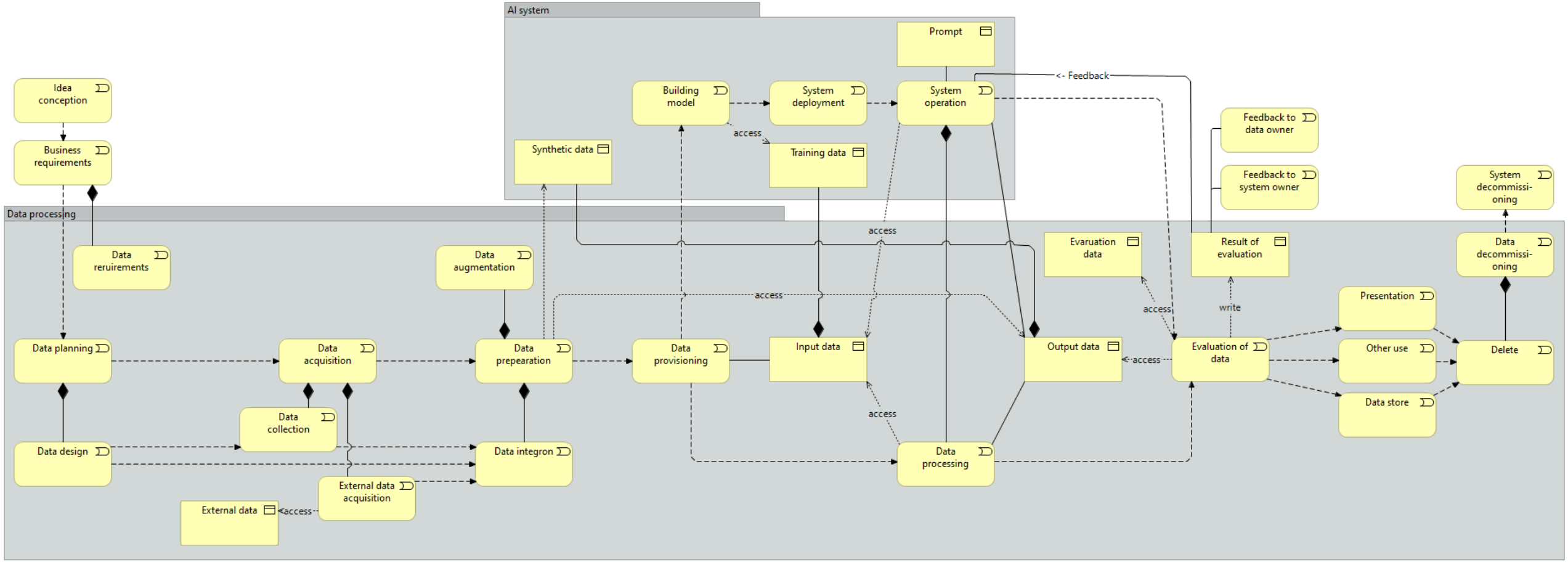
- Availability
- Portability
- Recoverability

**Additional data quality characteristics**

- Auditability
- Balance
- Diversity
- Effectiveness
- Identifiability
- Relevance
- Representativeness
- Similarity
- Timeliness

# ⑤ Process

- There are various standards for defining the life cycle. Here, we will organize them into the following detailed life cycles.

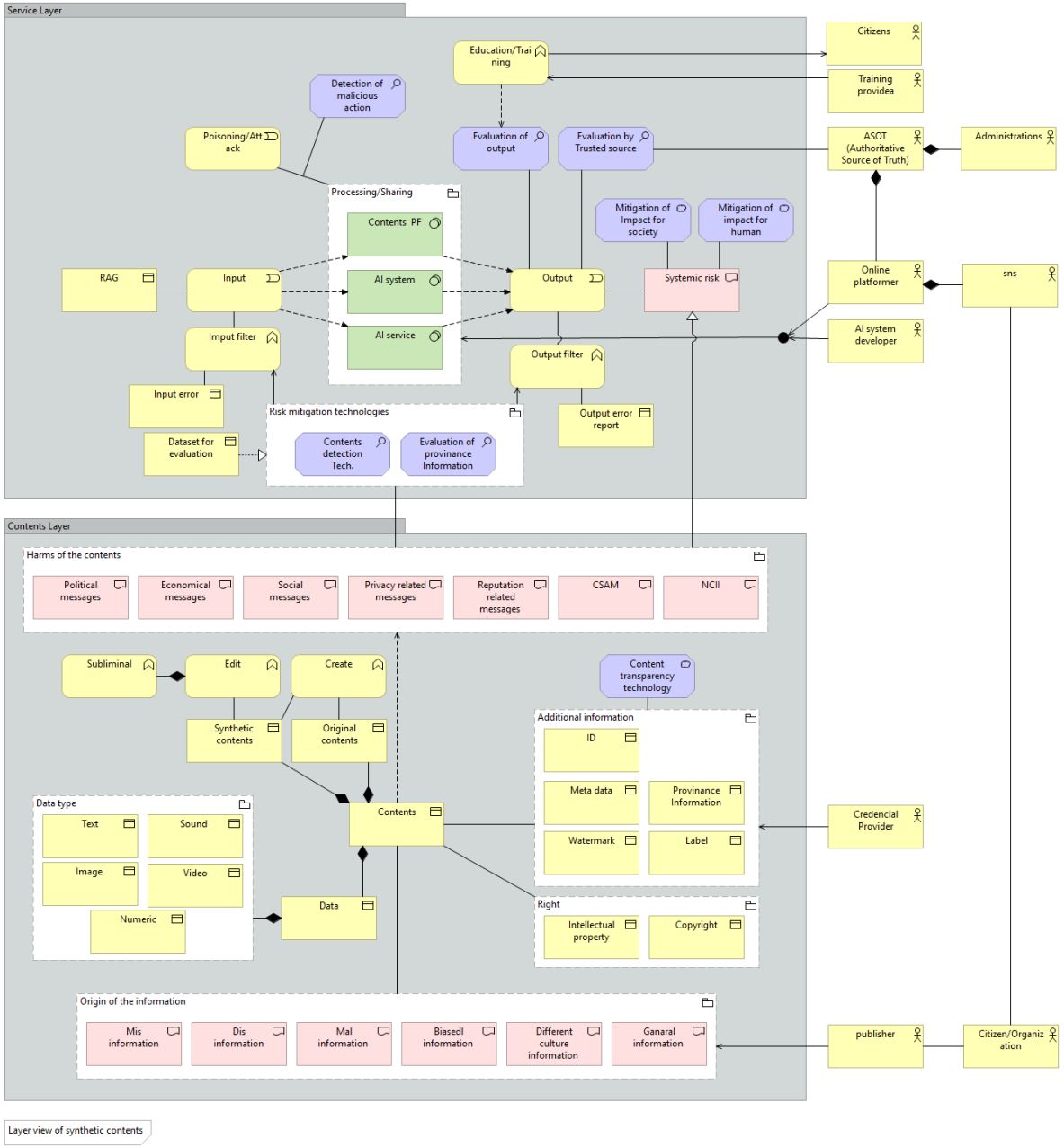



Data lifecycle
This lifeccycle refer the following standards.
ISO5259 Data quality for analytics and machine learning
ISO25024 Systems and software engineering-SQuaRE-Measurement of data quality
ISO8183IT-AI-Data life cycle framework

# ⑥ Contents management

- AI handles various data, and its stakeholders are diverse.

Enlarged image on next page



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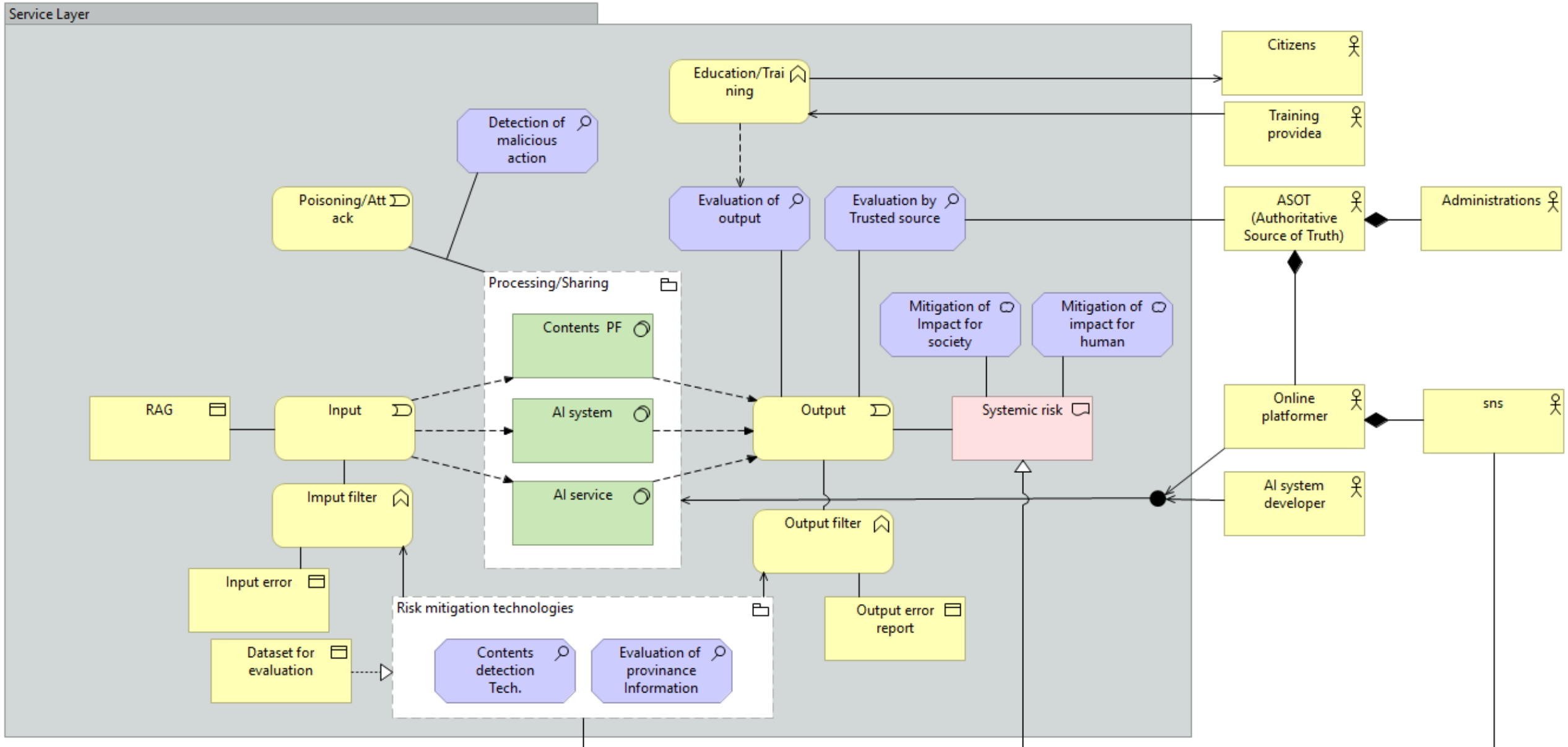

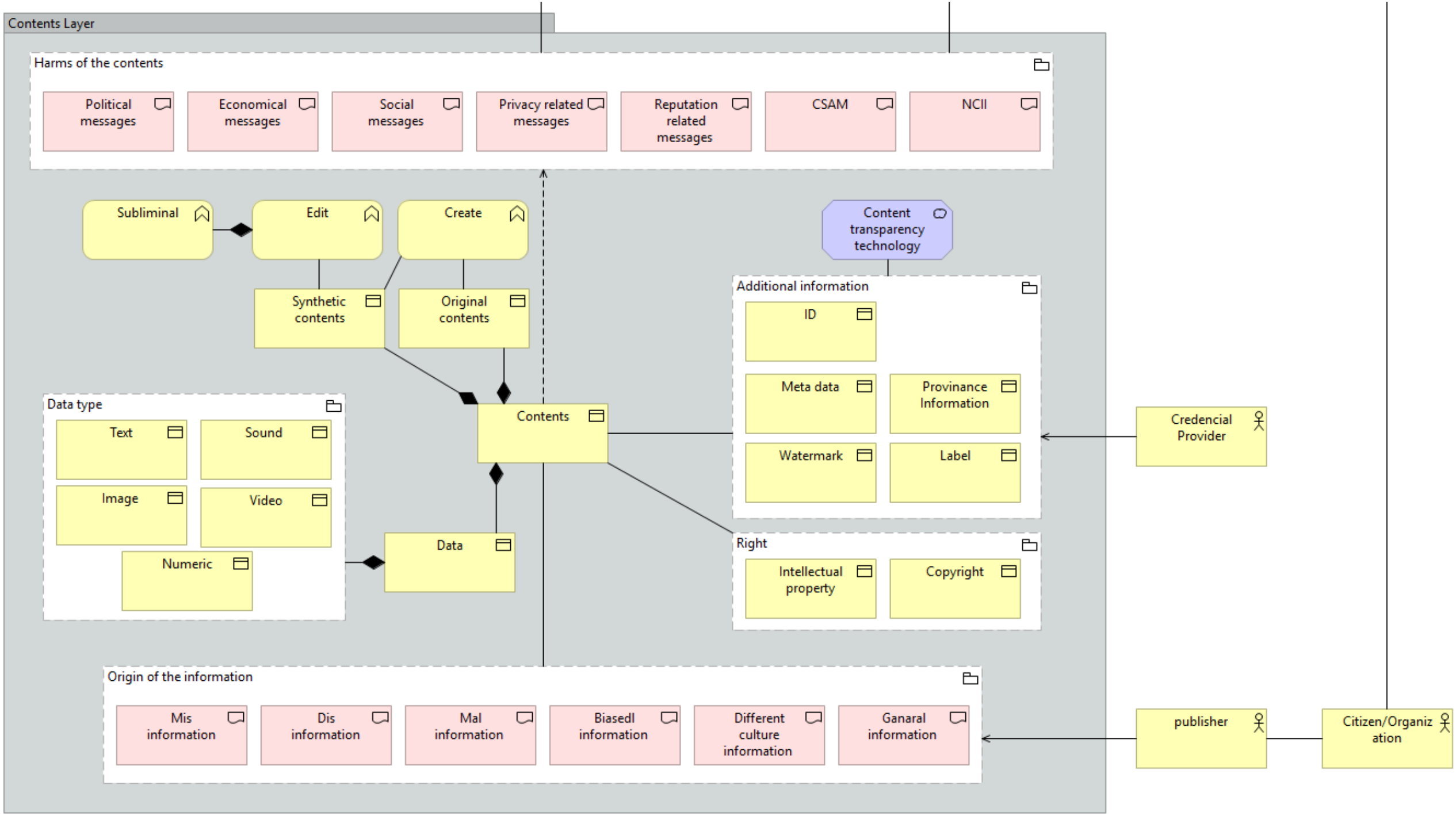
Contents Layer
Harms of the contents
Political messages
Economical messages
Social messages
Privacy related messages
Reputation related messages
CSAM
NCII
Subliminal
Edit
Create
Content transparency technology
Synthetic contents
Original contents
Additional information
ID
Meta data
Provinance Information
Watermark
Label
Data type
Text
Sound
Image
Video
Numeric
Contents
Data
Credencial Provider
Right
Intellectual property
Copyright
Origin of the information
Mis information
Dis information
Mal information
Biasedl information
Different culture information
Ganaral information
publisher
Citizen/Organization

# ⑦ Data quality management for AI

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- When managing data quality, accuracy, completeness, and timeliness are crucial. However, when using AI, special attention must be paid to the following points:

1. Annotation (Labeling) Quality Management
   - For machine learning, manual or automated labeling of data is indispensable. If there are many incorrect or inconsistent labels, it can lead to reduced model accuracy or skewed training results.
2. Checking for Bias and Ensuring Fairness
   - It is essential to verify that the data does not disproportionately represent certain attributes (e.g., gender, race, region) and to prevent such biases from being amplified during the training process.
3. Privacy and Security Measures
   - When handling data that includes personal or confidential information, proper anonymization and masking must be carried out, and secure storage and processing must be ensured. Additionally, privacy protection technologies (e.g., differential privacy) should be considered to prevent personal information from being inferred from trained models.

# ⑦ Data quality management for AI(Cont.)

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4. Data Version Control and Drift Management
   - AI models are trained based on the data distribution at the time of training. Over time, data distribution may change (“data drift”), which can cause a sudden drop in model performance. It is important to implement data version control, monitor distributions, and retrain or refine models as needed.
5. Handling Synthetic Data and Generated Content
   - In cases where real-world data is insufficient, synthetic data may be used. However, clarity regarding how it is generated and its quality is critical. Improper use of synthetic data can lead to flawed training and incorrect model outcomes.
6. Ensuring Explainability and Transparency
   - AI models should not function as a “black box.” Methods of Explainable AI (XAI) are required to clarify the decision-making process behind critical outcomes, enhancing trust and accountability.
7. Establishing Operational and Monitoring Frameworks
   - Continuous monitoring and maintenance are essential not only during data and model development but also throughout deployment. It is important to have systems in place that can respond quickly if unexpected bias arises or performance declines.

# Column: Bias

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Reducing bias is essential for implementing AI.

1. Preventing Unfairness and Discrimination
   - AI trained on biased data may make decisions that disadvantage specific groups based on gender, age, race, or location, leading to ethical concerns.
2. Ensuring Trust and Fairness
   - Bias undermines trust in AI systems. To create trustworthy AI solutions, fairness and impartiality must be maintained.
3. Avoiding Business Risks
   - Bias-related controversies can harm a company's reputation and expose it to legal risks.
4. Minimizing Societal Impact
   - The widespread adoption of AI amplifies its societal influence. If biased, AI can exacerbate inequalities or deepen societal divides.
5. Compliance with Legal and Ethical Standards
   - Increasing regulations around AI emphasize fairness and bias mitigation. Non-compliance can lead to penalties or exclusion from specific markets.

- By addressing bias, AI systems can foster broader societal acceptance, ensure ethical use, and maintain long-term reliability and sustainability.

# Column: Synthetic data

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The synthetic content generated by AI has a significant impact

1. Spread of Fake News and Misinformation
   - Synthetic content can generate highly realistic images, audio, and text, which may be misused to spread false information intentionally.
2. Invasion of Privacy
   - Technologies like deepfakes can create content that mimics an individual's face or voice, potentially violating their privacy.
3. Damage to Brand or Corporate Reputation
   - Maliciously created synthetic content can tarnish a company’s or brand’s reputation.
4. Legal Risks and Ethical Challenges
   - The creation and distribution of synthetic content can lead to legal and ethical issues such as copyright infringement, violation of publicity rights, or generation of discriminatory content.
5. Decline in Trust
   - An abundance of synthetic content makes it harder for consumers and businesses to trust digital content.
6. National Security and Political Risks
   - Synthetic content might be misused politically.

# III. Implementation

The things should be done at each stage of the process defined in II. ⑤

# Implementation

- Operation

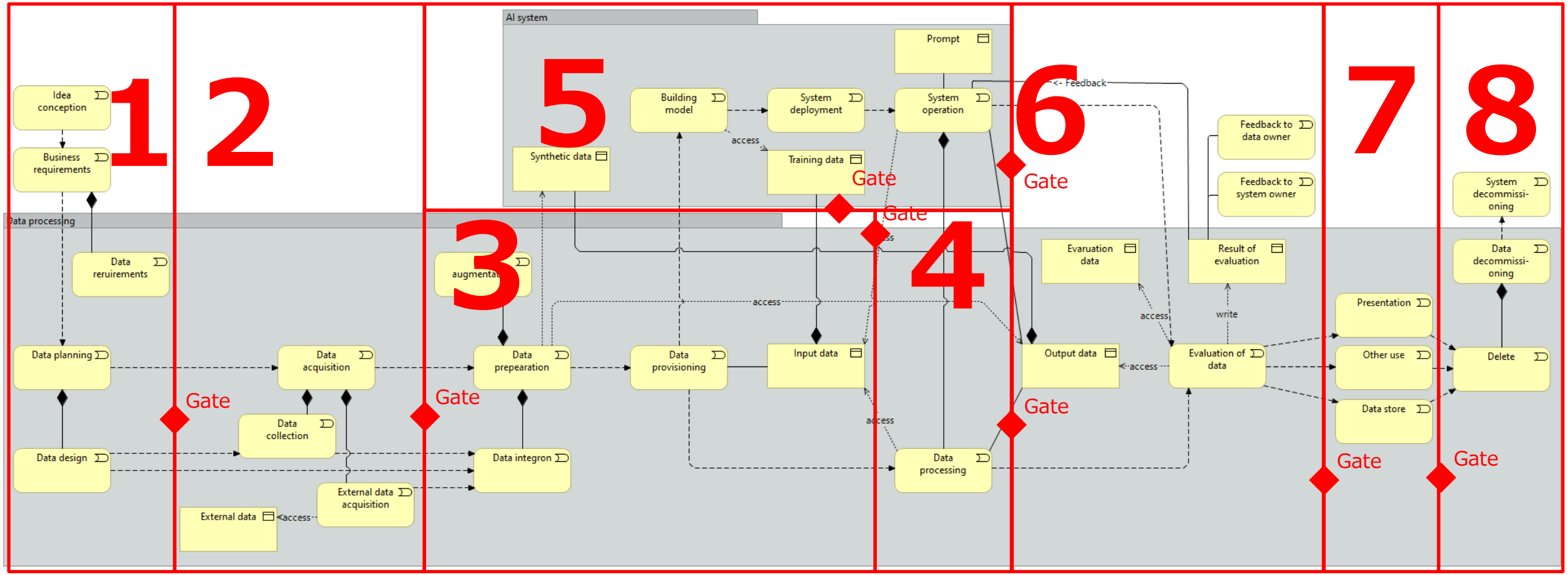
# Process

1.Data planning
2.Data acquisition

3.Data preparation
4.Data processing
5.AI system

6.Evaluation of output

7.Deliver the result
8.Decommisioning




Data lifecycle
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ISO8183IT-AI-Data life cycle framework

# Role of stakeholders

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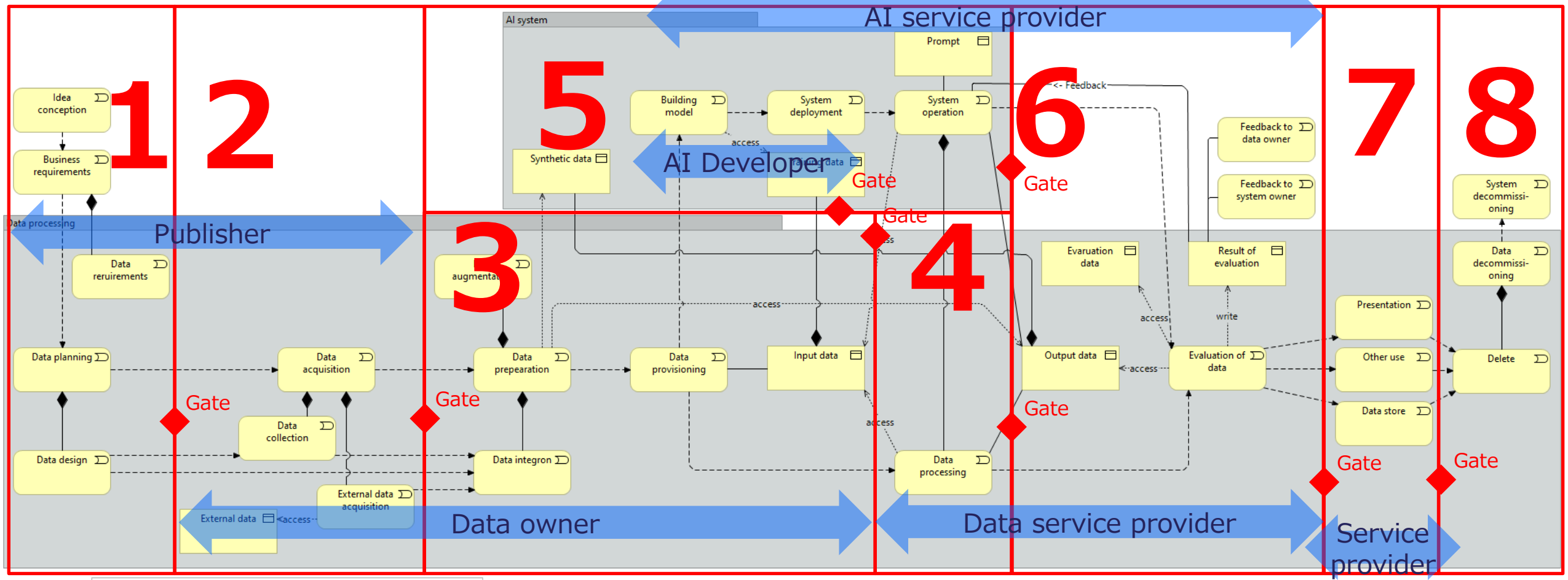
1.Data planning
2.Data acquisition

3.Data preparation
4.Data processing
5.AI system

6.Evaluation of output

7.Deliver the result
8.Decommisioning



# 1.Data planning

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## Description

- This is a critical phase in the data lifecycle.
- Clearly define the intentions and motivations behind the need for the data.
- Establish interoperability across the entire service and ensure scalability for future growth.
- Specify the data lifecycle, including acquisition methods, evaluation methods, and disposal processes.

**Issue**

- Managing and organizing existing data effectively.
- Revising and updating rules and processes to align with current needs.
- Leveraging new technologies to optimize data management practices.

**Requirement**

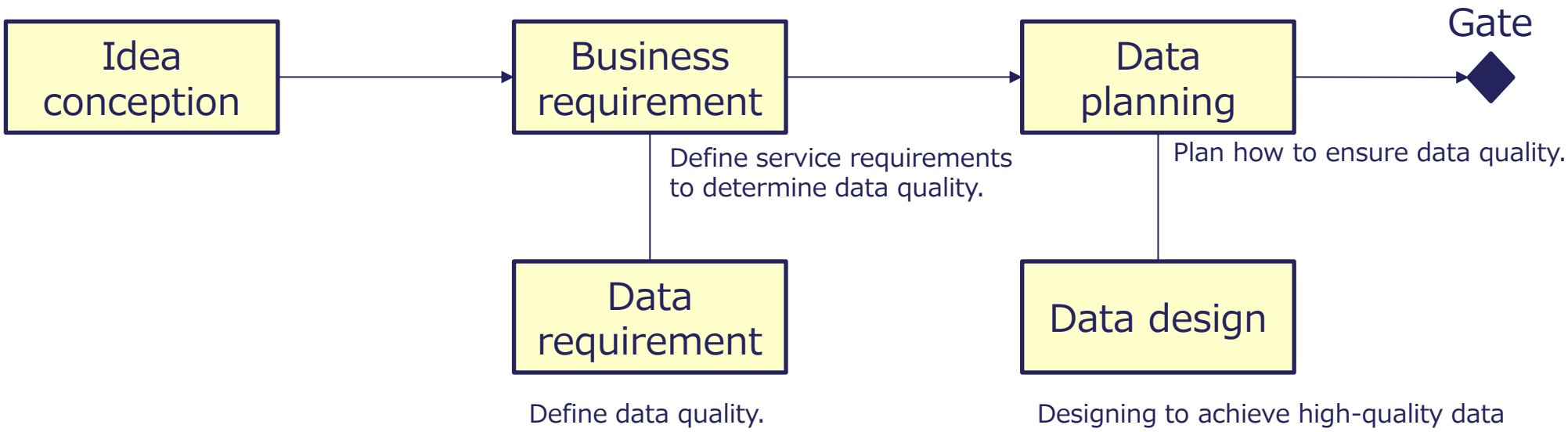
- High-quality data, including standardized and well-structured formats.
- Mechanisms to ensure interoperability between systems and services.
- A reliable and authoritative "source of truth" for data consistency.

**Value**

- Enhanced efficiency in downstream processes through better-prepared data.
- Greater sustainability and scalability of the overall service architecture.

# Actions

- Quality is built in three steps, from concept creation to requirements definition and design.




Validation and verifications | Change management | Configuration management | Risk management

Determine methods for data validation, change management, configuration management, and risk management throughout the data lifecycle.

Data planning

# Procedure and checkpoint

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| Procedure | Checkpoint |
| --- | --- |
| **Idea conception**<br>1. Gather the user needs<br>2. Create a concept<br>3. Define the business and data policy<br>  • Align to the organizational policies<br>  • Check the future trend<br>4. List up the stakeholders<br>5. Check the feasibility | ☐ Do decision-makers understand the overall system concept?<br>☐ Do decision-makers understand the benefits of high data quality?<br>☐ Do decision-makers understand the risks posed by low data quality?<br>☐ Do decision-makers understand the costs of requiring higher data quality than necessary and the importance of balancing effectiveness and cost?<br>☐ Do you have organisational capacity and skilled personnel? |
| **Business requirement**<br>1. Define the business objective and scope<br>2. Define the value, requirement, constrain and risk. | ☐ Is service quality clearly defined? |

Data planning

# Procedure and checkpoint

AISI Japan AI Safety Institute

## Procedure

**Data requirement**

1. Define the related data
   - Input, Output, Reference
   - Constrain, Interface, Statistical data
2. Make the specification of the data
   - Description, Goal, Requirement, Matters to consider
   - Refer ISO/IEC5259-3 Data specification
3. Define the required quality level
   - Accuracy, Completeness, Consistency, Credibility, Currentness
   - Accessibility, Compliance, Confidentiality, Efficiency, Precision, Traceability, Understandability
   - Availability, Portability, Recoverability
   - Auditability, Balance, Diversity, Effectiveness, Identifiability, Relevance, representativeness, Similarity, Timeliness
   - Refer ISO/IEC5259-2 characteristics

## Checkpoint

- ☐ Are the data required by the business listed?
- ☐ Have quality control items been defined for each data?
- ☐ Are the data quality requirement levels for each data defined?

Data planning

# Procedure and checkpoint

AISI Japan AI Safety Institute

Procedure

**Data planning**

1. Check the existing data.
2. Gather the needs for data
3. Define the master data
4. Define the data architecture
5. Define the design policy and methodology
   - Structure, Location, Modeling, Documentation
6. Define and find the data source
7. Check the data-related legislations

Checkpoint

- ☐ Do decision-makers agree to convert existing data into the new model?
- ☐ Are stakeholders' data needs understood?
- ☐ Are the data architecture and design policies documented?
- ☐ Are the required data defined and available?
- ☐ Have legal constraints on the use of the data been checked?

Data planning

# Procedure and checkpoint

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Procedure

**Data design**

1. Check the reference models and taxonomy
2. Design the data models and the taxonomy
3. Design the metadata and Labels
4. Design the rule
5. Check the compliance for legislations

Note:

In Japan, GIF(Government Interoperability Framework) provides reference models.

Checkpoint

- ☐ Do you refer to a data reference model or standardised taxonomy?
- ☐ Do you use modelling tools?
- ☐ Are metadata designed on a DCAT basis?
- ☐ Do you refer to general rules for utilisation and access?
- ☐ Are they designed to comply with legislation?

# Column: Reference model

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- A reference model is a conceptual framework that provides standardized structures, processes, and data frameworks for a specific industry or domain. It serves as a "template" for designing and implementing systems or processes, offering unified terminology, definitions, and methods. This enhances interoperability between organizations and systems, improving efficiency in development and operations. Due to its high level of abstraction, a reference model can be applied to a wide range of scenarios and customized to meet specific requirements.

- How a Reference Model Improves Data Quality
  - A reference model establishes a foundation for data consistency and standardization.
  - By adopting common data definitions and naming conventions, it prevents inconsistencies between different systems.
  - Additionally, utilizing a reference model eliminates data duplication and redundancy, enabling the creation of an efficient and streamlined data structure.
  - By embedding governance rules and constraints aligned with business processes, it enhances the accuracy and integrity of the data.
- Reference models play a critical role in ensuring data completeness during the design phase and reducing errors and correction costs during the operational phase.

# Column: Data dictionary

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- Data Dictionary is a repository that systematically organizes and manages the names, definitions, formats, and relationships of data elements used in information systems and databases. It defines attribute names, data types, lengths, constraints, and business rules for each data element, providing consistent standards across the organization.

- This shared understanding of data meaning and structure among stakeholders—such as developers and operators—helps streamline system development and operations, improving efficiency and quality.
- Moreover, during data mapping and system integration, it enhances the accuracy of data migration and reporting between different systems, making it easier to maintain consistency.
- In terms of data governance, a Data Dictionary serves as the foundation for security requirements, access rights, and regulatory compliance.
- By keeping it up to date, organizations can flexibly accommodate new data requirements and swiftly adapt to changing business needs, ensuring a robust and responsive system environment.

# Column: Modeling

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- Data modeling is the process of visually and logically organizing the data used in information systems and databases, representing its structure and relationships in the form of a model. It involves defining entities (data objects), attributes (data elements), and relationships (connections between data). Data modeling typically includes three levels: conceptual data models (representing data from a business perspective), logical data models (defining detailed structures from a technical perspective), and physical data models (concretizing the database structure).
- Data Modeling Contributes to Improved Data Quality.
  1. Ensures Consistency and Standardization
  2. Eliminates Duplication and Redundancy
  3. Improves Data Integrity and Consistency
  4. Enhances Data Reusability
  5. Improves Decision-Making Quality
- Data modeling is not just a technical process; it is a critical activity that underpins data quality management and data governance.

* Apart from data modelling, there is AI modelling; AI modelling refers to AI training data.

# 2.Data acquisition

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## Description

- This step involves generating, collecting, and sourcing data from external systems or entities.
- Prevent errors during data acquisition, whether from sensors or manual data input.
- Ensure poor-quality data is excluded when obtaining data from external sources.
- When supplementing data with synthetic data, clearly document the process and prevent the inclusion of inappropriate synthetic content.
- Add metadata, such as data profiles and provenance information, to ensure traceability and data quality.

**Issue**

- Inclusion of low-quality or inappropriate data during data collection can compromise the reliability of the dataset.

**Requirement**

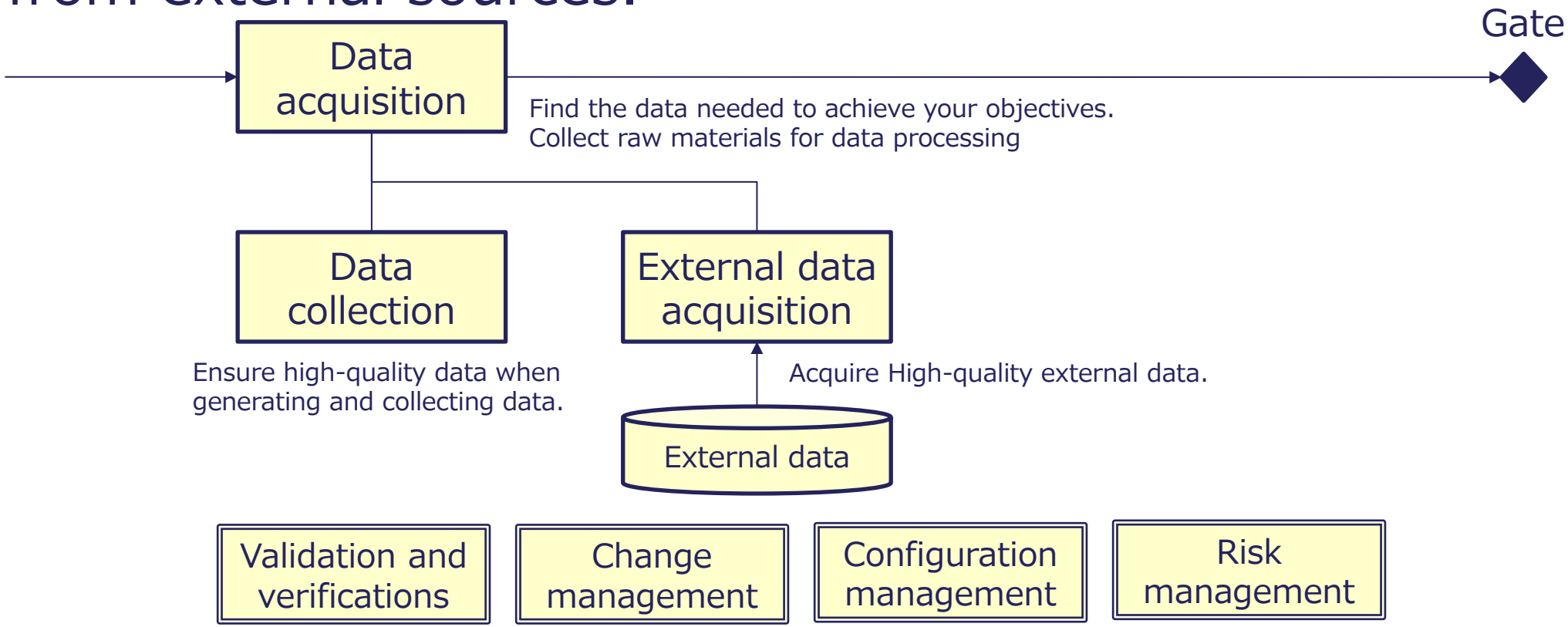
- Efficiently collect high-quality data to minimize inaccuracies.
- Reduce the need for extensive pre-processing steps such as data cleansing by maintaining quality at the point of acquisition.

**Value**

- Reduction in time and costs associated with data preparation and cleaning.
- Increased trust in the data, leading to better decision-making and enhanced credibility for AI applications.

# Actions

- Generate and collect the data required to achieve the objective, and if the data is not available within the organisation, acquire it from external sources.



Data acquisition

# Procedure and checkpoint

AISI Japan AI Safety Institute

Procedure

**Data acquisition**

1. Finding the necessary data
2. Check the provenance information
3. Check the condition

**Data collection**

1. Check the device (Sensor)
2. Collect/Input the data
   - Prevent the errors by using the web forms and APIs
3. Verify the data
   - Removal of out-of-range data and inappropriate data
   - Lack of consistency
4. Anonymise and conceal
5. Make the metadata
   - General information
   - Quality information
   - Method of measuring or gathering data

Checkpoint

- ☐ Are data obtained from reliable sources?
- ☐ Are there any problems with the data's provenance information?
- ☐ Are there any restrictions on the conditions of use of the data?

- ☐ Are you taking steps to prevent inappropriate data from entering data?
- ☐ Do you ensure that out-of-range data is not entered?
- ☐ In the case of sensor data, is it calibrated?
- ☐ Do you check that the data is consistent?
- ☐ Do you follow DCAT for metadata?
- ☐ Do you describe the method of measurement and collection of data?

Data acquisition

# Procedure and checkpoint

AISI Japan AI Safety Institute

## Procedure

**External data acquisition**

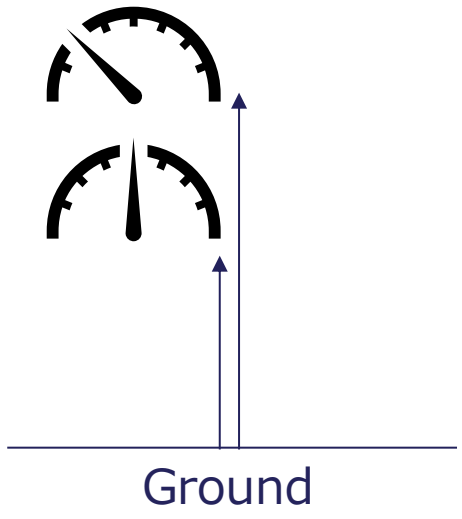
1. Check the metadata and provenance information
2. Velify the data
   - Checking quality characteristics
   - Finding inappropriate content (including synthetic content)
3. Add metadata and provenance information

## Checkpoint

- ☐ Is the data provision reliable?
- ☐ Is the data clear on provinance information?
- ☐ Does the quality of the data meet specifications?
- ☐ Are there any non-convertible data items?
- ☐ Does it contain data inappropriate to the system's objectives?
- ☐ Does the data contain important information other than the data items to be imported?
- ☐ Does it contain synthetic data that is not explicitly identified as synthetic data?

# Column: Sensor data

- Sensors are used in various environments, including outdoors and inside equipment. In addition, the measurement method will also make a difference, so it is necessary to manage the data collection according to the sensor.




The same place, but the values differ depending on the height measured and the device used.

| Category | Device-dependent quality measurement quantity | Description |
|---|---|---|
| Design information | Device information | Level of understanding of the measurement principles, processing methods, etc. for the physical quantities (light, sound, etc.) input to the device |
| | Fault-tolerance | Level of device operation |
| | Durability | Level of decline in serviceable parts |
| | Security measures | Level of implementation of security measures |
| | Communication stability | Level of operation without communication interruption or delay |
| Installation and adjustment | Appropriateness of installation method | Level of implementation of appropriate installation according to conditions |
| Operation and maintenance | System stability | Level of operation stability |
| | System environment monitoring | Level of installation status monitoring |
| | Appropriateness of updates | Level of ppropriate software version operation |

White Paper “Study for Formulating Guidelines for Evaluating the Quality Level of Sensing Data”, Data Sharing Association, Japan

# Column: Provenance data

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- Provenance data refers to information that records the history and origin of data, including its creation, transformation, movement, and usage. It tracks who created, modified, or used the data, as well as when and how these actions occurred. Provenance data serves as metadata to enhance transparency in data processing, making it particularly valuable in fields like healthcare, finance, and scientific research where data reliability and integrity are critical. This information typically includes the data's source, processing history, applied business rules or algorithms, and associated systems or users.

- How Provenance Data Improves Data Quality
  - Provenance data ensures data reliability by making its history transparent.
  - By clarifying the origins and lifecycle of the data, it becomes easier to validate its accuracy and appropriateness, and to identify errors or tampering.
  - It also provides insights into data creation and updates, enabling the correction of inconsistencies or incomplete records.
  - Additionally, in audits and compliance processes, provenance data serves as evidence that the data has been handled appropriately, boosting confidence in its use.
- This enhances the accuracy and effectiveness of data analysis and decision-making, while also mitigating risks and strengthening the foundation of data governance.

# 3. Data preparation

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## Description

- It is the final stage of providing quality data.
- Cleanse the prepared data: Remove any erroneous or out-of-range data and adjust taxonomy conversions, semantics, and granularity.
- Supplement lacking data as necessary.
- Integrate the cleansed data into a unified dataset.
- Add watermarks to the data, if needed, to ensure data authenticity and integrity.
- Create additional data for data augmentation using machine learning techniques.

**Issue**

- The definition and quality of the data need to be refined and standardized.
- The data profile may be unclear or incomplete.
- Data quality may be insufficient, or key data elements may be missing.

**Requirement**

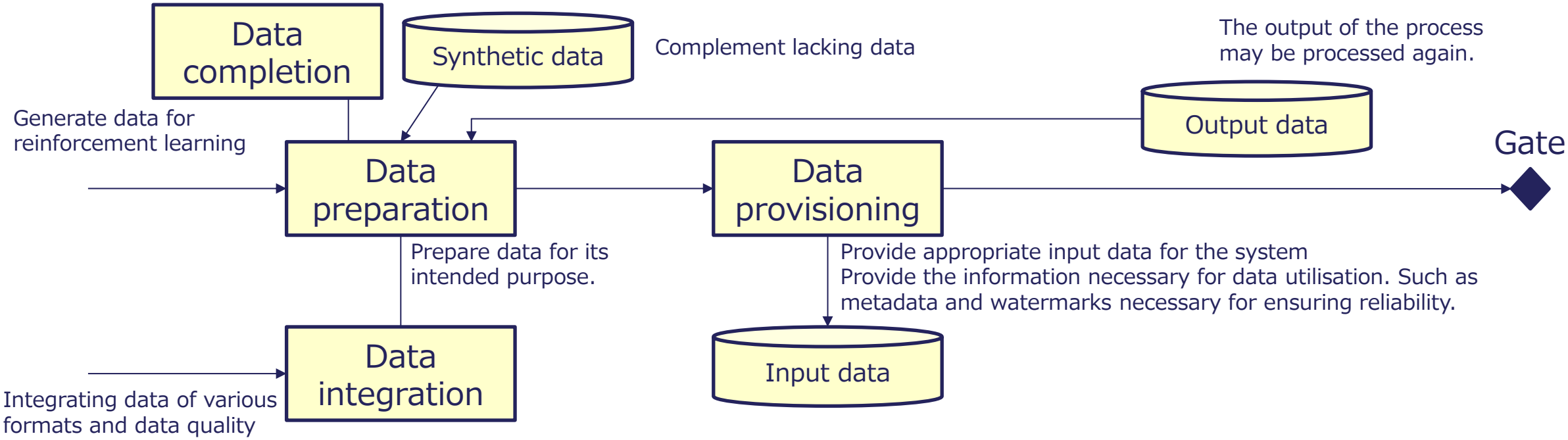
- Data of appropriate quality for intended use.
- Comprehensive and accurate metadata about the data.
- Provenance information to trace the source and transformation history of the data.
- Assurance of data authenticity and reliability.

**Value**

- Enables accurate and reliable processing by ensuring high-quality input data.
- Facilitates data validation, confirmation, and traceability throughout the AI workflow.

# Actions

- Various data is integrated to create input data. Input data is used as training data or data to be processed.




Validation and verifications | Change management | Configuration management | Risk management

Change management and configuration management become important. In particular, sensor data is real-time data, so consideration is needed for its management.

Data preparation

# Procedure and checkpoint

AISI Japan AI Safety Institute

| Procedure | Checkpoint |
| --- | --- |
| **Data preparation**<br>1. List the collected data<br>2. Decide on the data integration policy<br>3. Decide on the data supplementation policy<br>4. Data cleansing<br>5. Add label | ☐ Are all necessary data listed?<br>☐ Is a data integration policy in place?<br>☐ Is there a defined policy for data supplementation? |

Data preparation

# Procedure and checkpoint

AISI Japan AI Safety Institute

Procedure

**Data integration**

1. Decide on the data model after integration
2. Create conversion tables for taxonomys and controlled vocabulary
3. Check the semantics of data items and decide on the matching method
4. Adjust accuracy and units
5. Convert data format (xml, json, csv,-)
6. Create notes describing the differences in semantics
7. Create metadata related to integration

Checkpoint

- ☐ Has the conversion table been created taking into account the meaning of the data items?
- ☐ Is the division of data done in a logical way?
- ☐ Are there priority rules for duplicate data?
- ☐ Is blank data set to no data?
- ☐ Is data conversion carried out automatically by tools?
- ☐ Is the consistency of integrated data checked?
- ☐ Is metadata created by DCAT?

Data preparation

# Procedure and checkpoint

AISI Japan AI Safety Institute

| Procedure | Checkpoint |
| --- | --- |
| **Data completion**<br>1. Analyze the state of the data and determine whether it needs to be supplemented.<br>2. Add the complement data | ☐ Are you using appropriate data to supplement the data? |
| **Data augmentation (for AI system)**<br>1. Prepare the base data<br>2. Generate the training data based on the base data | ☐ Is there any bias in the base data?<br>☐ Is there a bias caused by reliance on a small number of base data? |
| **Synthetic data acquisition**<br>1. Check the metadata and provenance information<br>2. Validate the data | ☐ Is it clearly indicated that it is a snthetic content?<br>☐ Does it contain inappropriate or unconsent content? |

Data preparation

# Procedure and checkpoint

AISI Japan AI Safety Institute

| Procedure | Checkpoint |
| --- | --- |
| **Data provisioning**<br>1. Register catalogue information<br>2. Provide data interface<br>3. Control the version<br>4. Provide data samples<br>5. Add content protection information such as watermarks<br>6. Operate the access control function<br>7. Track the usage, if nessesary | ☐ Is the data provided in a machine-readable interface?<br>☐ Do you include mechanisms such as watermarking to make it difficult for data to be misused?<br>☐ Are access controls in place to prevent unauthorised use? |

# Column: IDs

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- Assigning unique identifiers (IDs) to data is critical for improving data quality. By tagging each record with an ID, you make it possible to integrate information from multiple sources and ensure consistent data management across systems.
- This prevents confusion or duplication when similar or related pieces of data need to be merged or compared. For example, if two departments track customers in separate databases, using the same customer ID allows the two datasets to be combined accurately.
- In addition to aiding data integration and consistency, assigning IDs provides several other benefits:
  1. **Traceability and Auditability**: A unique ID makes it easier to trace the origin and history of a data record, which helps in audits and compliance checks.
  2. **Efficient Updates**: When you need to update or delete specific data, having an ID allows for quick and precise identification of the target records.
  3. **Scalability**: As data grows, unique IDs ensure that new records can be added without conflicts or confusion, helping maintain clarity in large-scale databases.
  4. **Enhanced Data Governance**: IDs support clearer ownership and governance policies, since you can assign responsibility for specific records to the appropriate teams or systems.
- Overall, using IDs is a fundamental practice that not only enables reliable data integration and consistency but also improves the overall manageability and value of your data.

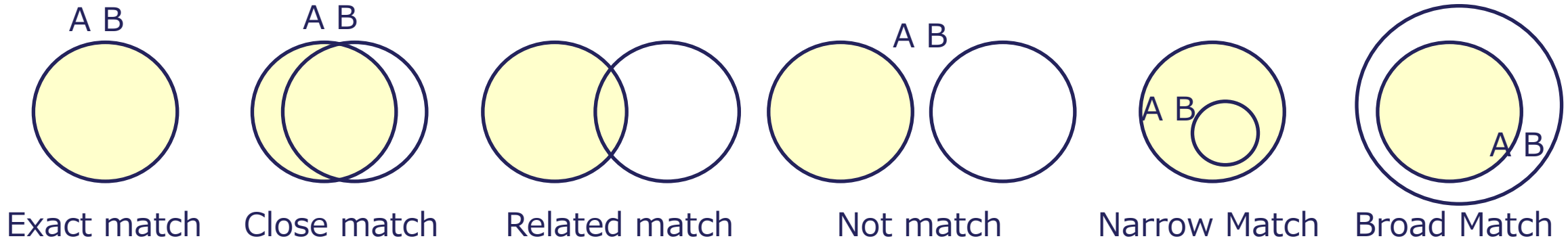
# Column: Data cleansing

AISI Japan AI Safety Institute

- Data cleansing is the process of identifying, correcting, or removing errors, inconsistencies, and inaccuracies in datasets to improve data quality and reliability. It ensures that data is complete, accurate, and consistent, making it more suitable for analysis, reporting, and decision-making. Data cleansing involves addressing issues such as missing values, duplicate records, incorrect formatting, and outliers. This process is crucial for maintaining the integrity of data, especially when integrating multiple datasets or preparing data for advanced analytics.
- Data Cleansing Techniques
  - Removing Duplicates: Identifying and eliminating duplicate records to avoid redundant or misleading data.
  - Handling Missing Data: Filling in missing values using techniques like interpolation, imputation, or deletion where necessary.
  - Standardizing Data: Ensuring data follows consistent formats, such as standardizing date formats or capitalization.
  - Validating Data: Checking data against predefined rules or reference datasets to ensure accuracy and consistency.
  - Correcting Errors: Identifying and rectifying typos, incorrect entries, or mismatched values.
- Effective data cleansing ensures high-quality data, leading to better insights and more accurate decision-making.

# Column: Data matching

- Data matching is the process of comparing and identifying records from different datasets or within the same dataset to determine if they represent the same entity. It is widely used in scenarios like deduplication, linking customer information across systems, fraud detection, and data integration. Data matching involves evaluating attributes such as names, addresses, phone numbers, or other identifiers to detect matches, even when there are slight variations or inconsistencies in the data. The level of matching is sometimes expressed as a score.
- By consolidating duplicate or related records, data matching improves data quality and ensures accurate analysis and reporting.



# Column: Data completion

AISI Japan AI Safety Institute

- **Data augmentation** is a technique used to enhance the size and diversity of a dataset by applying various transformations to existing data. These transformations can include rotating, flipping, cropping, or adjusting brightness and contrast for image data, or adding noise, paraphrasing, or back-translation for text data. The goal is to increase the variety of training data, which helps improve the performance and robustness of machine learning models.

- **Data enrichment** is the process of enhancing existing data by supplementing it with additional information from external or internal sources. This process adds value to raw data by making it more comprehensive, accurate, and useful for analysis or decision-making. Enrichment often includes adding missing data points, improving data accuracy, or integrating contextual information such as demographic, geographic, or behavioral data.

# Column: Content Transparency Tech.

AISI Japan AI Safety Institute

- Content Transparency Technologies refer to tools, frameworks, or systems designed to provide clarity, authenticity, and accountability in digital content. These technologies aim to ensure that users can understand the origin, context, and reliability of the information they encounter. They are often used in media, advertising, social platforms, and data-driven industries to address issues such as misinformation, biased content, or opaque algorithms.
- Key features of Content Transparency Technologies include:
  - Source Verification: Ensuring content authenticity by verifying the origin or creator of the material.
  - Traceability: Providing a clear history of edits, ownership, or dissemination of the content.
  - Content Labeling: Adding metadata or markers to indicate whether content is sponsored, user-generated, or machine-generated.

# Column: Indication of data quality

AISI Japan AI Safety Institute

- Data quality is sometimes managed in detail by data producers and users, but simple indicators are also required when data is circulated in society.
- For example, home appliances are managed using detailed quality indicators during the manufacturing process, but simple indicators are shown to consumers at the stores where the finished products are sold.
- There are many characteristic indicators available for data quality management, but it is necessary to consider simple indicators for use in trading markets, as well as detailed indicators for use in production management.


The indicators to be used depend on the purpose.

# 4. Data processing

AISI Japan AI Safety Institute

## Description

- Create service value by processing data effectively and efficiently.
- In the event of an error, identify its root cause within the data path and provide actionable feedback to ensure prompt resolution.
- The workflow emphasizes maintaining data integrity and seamless operation throughout the processing pipeline.

**Issue**

- Errors such as data inconsistencies, mismatches, or incomplete records can arise, leading to disruptions in the processing pipeline.
- These challenges make it difficult to maintain the reliability and accuracy of the processed data.
- Additionally, identifying the root cause of errors can be time-consuming without robust diagnostic tools or clear process models.

**Requirement**

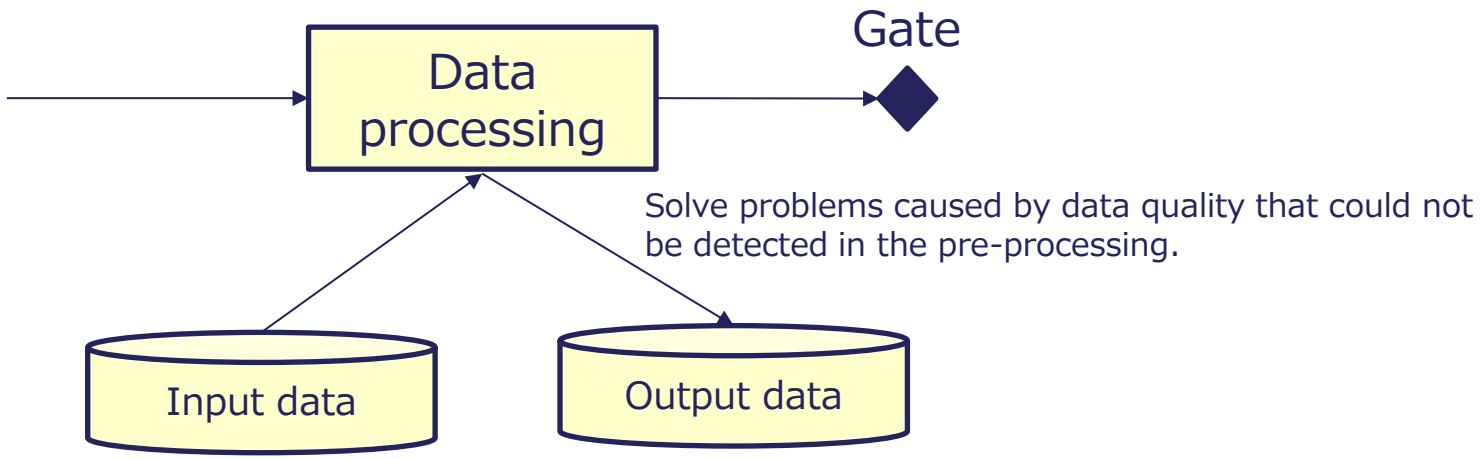
- Develop comprehensive processes and robust data models to efficiently identify and address the root causes of errors.
- The workflow must support real-time monitoring and diagnostics, enabling quicker error resolution and minimizing service disruptions.

**Value**

- By addressing errors effectively and ensuring high-quality data processing, this workflow enhances the accuracy and trustworthiness of services.
- It builds customer confidence, reduces operational risks, and supports data-driven innovation, ultimately creating greater value for both the organization and its stakeholders.

# Actions

- Process the data that has been input. As there is a possibility of data inconsistencies occurring during the processing, a feedback mechanism is required.




Validation and verifications | Change management | Configuration management | Risk management

Errors found in processing may also affect existing processing. It is necessary to investigate the cause from the perspective of risk.

Data processing

# Procedure and checkpoint

AISI Japan AI Safety Institute

Procedure

**Data Processing**

1. Checking consistency
2. Processing data
3. Reporting errors in processing

Checkpoint

- Is an error notified when there is an anomaly in the data?
- Is the processing process visualised so that data can be verified?

# 5. AI system

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## Description

- Learn from training data to create AI models.
- Implement, utilize, and operate these models.
- Relearn and refine models based on the evaluation of their outputs.
- Use Retrieval-Augmented Generation (RAG) techniques to improve the quality of training data, thereby enhancing the accuracy and reliability of outputs.

**Issue**

- Hallucination: AI models may produce false or inaccurate information, especially when data is limited or unclear.
- Outputs may show societal or data biases, raising issues of fairness, inclusion, and ethics.
- The time, resources, and oversight needed for training and relearning are high, potentially reducing scalability.

**Requirement**

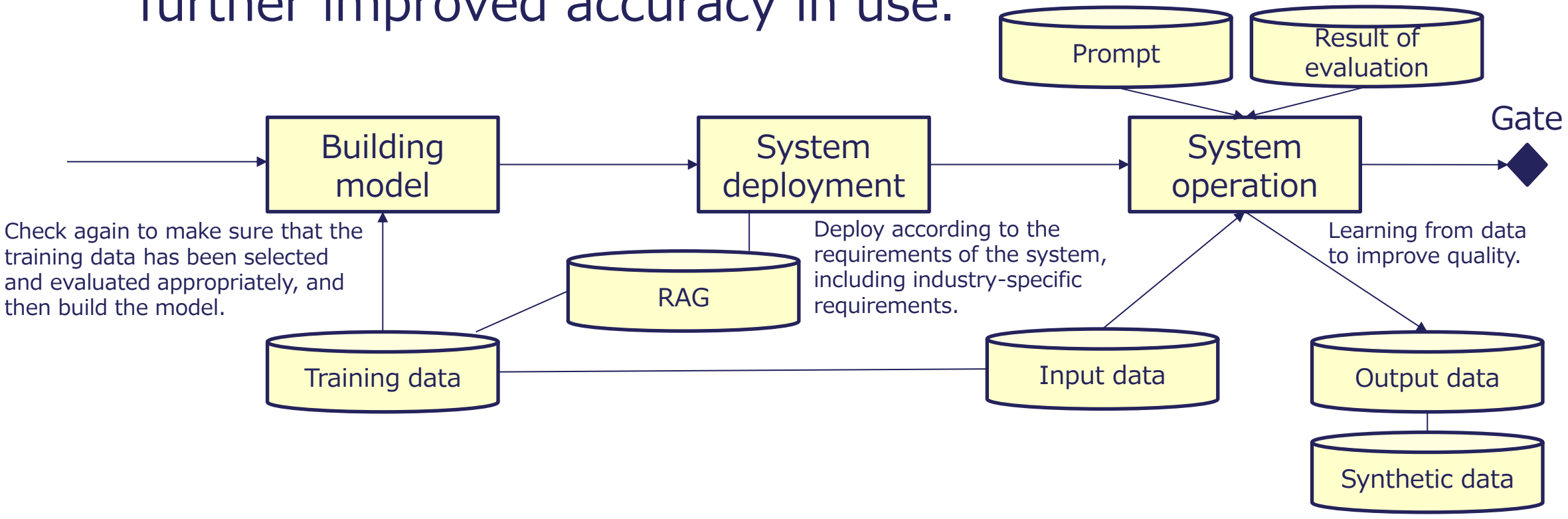
- Accurate and Reliable Answers: AI systems must consistently provide correct and precise responses to user queries.
- Supporting Reference Information: Outputs should include verifiable sources or reasoning to build trust and ensure transparency in the decision-making process.

**Value**

- High Service Level:By providing accurate, fast, and contextually relevant responses, the system can achieve a high level of user satisfaction and operational excellence.
- Trust: Delivering reliable, unbiased, and transparent outputs fosters long-term trust in the AI system among users and stakeholders.

# Actions

- Input of high-quality data that is fit for purpose and further improved accuracy in use.




Re-validate the quality of training data, including RAGs, and manage their content. Also manage risks based on evaluation results.

AI system

# Procedure and checkpoint

AISI Japan AI Safety Institute

| Procedure | Checkpoint |
| --- | --- |
| **Building model**<br>1. Check the required level for AI<br>2. Decide the training data<br>• Prevent the bias data and Inappropriate data<br>3. Decide whether to use RAGs*<br>• *RAG (Retrieval-Augmented Generation)<br>4. Check whether there is any personal information or intellectual property information<br>5. Generate the model<br>6. Test the model | ☐ Do you use reliable data for your training data?<br>☐ Have you implemented RAGs to improve accuracy?<br>☐ If there is information that could lead to personal data or intellectual property, do you take measures to prevent this information from being displayed, for example by excluding the necessary information from the training data? |
| **System deployment**<br>1. Deploy the system<br>2. User training | |
| **System operation**<br>1. Operate the system<br>2. Continuous monitoring | ☐ By reusing the output, isn't there a bias in the AI? |

# 6.Evaluation of output

AISI Japan AI Safety Institute

## Description

- This phase serves as the final verification before the AI system's outputs are provided to end-users.It includes assessing the outputs for ethical considerations, information accuracy, potential biases, and alignment with intended purposes.
- Both automated systems and human reviewers evaluate outputs using reliable information sources and pre-established evaluation datasets.
- Errors identified during this process are reported back to the data owner or system owner to enable continuous improvement.

**Issue**

- AI system may produce inaccurate or inappropriate responses, reducing user trust and system reliability.
- Outputs can deviate from authoritative definitions or standards, causing inconsistencies.
- AI system requires robust mechanisms to detect, categorize, and correct errors.

**Requirement**

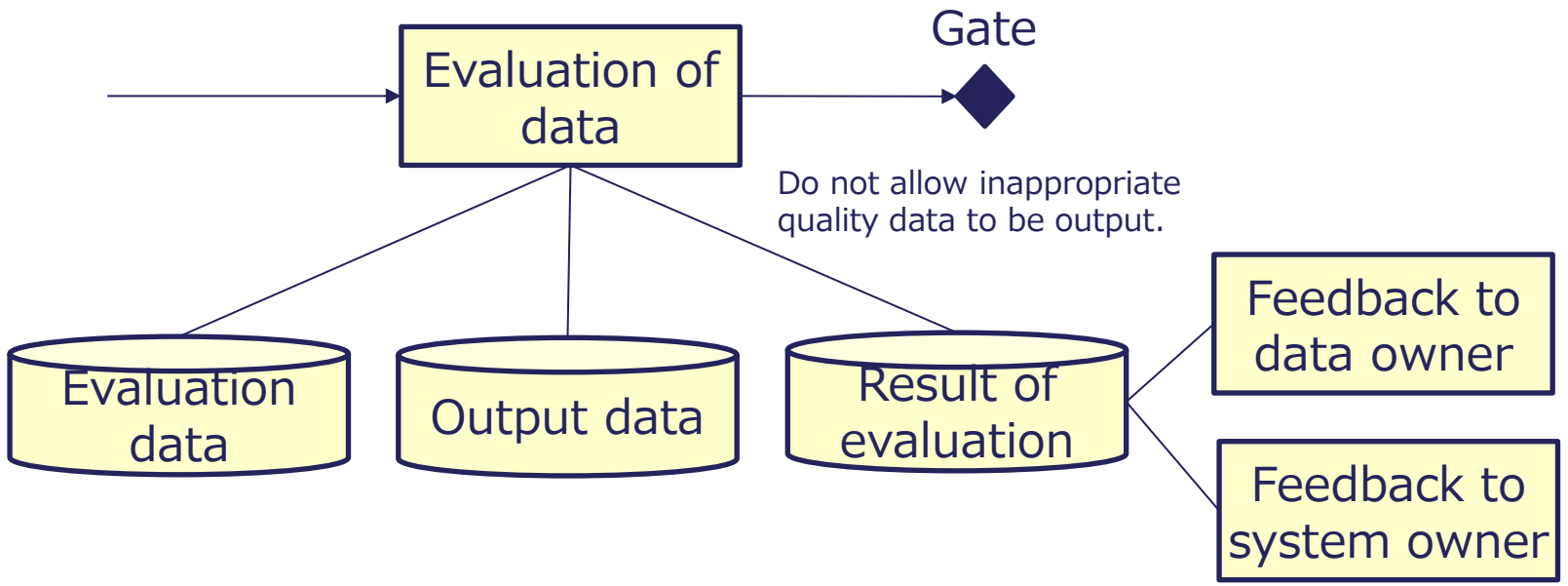
- Preventing inaccurate or inappropriate outputs requires robust measures to address accuracy, ethics, and bias.
- Outputs needing user confirmation should be flagged for clarity. Feedback loops are essential to prevent repeated errors and improve system performance.

**Value**

- High Service Levels: Deliver outputs that meet or exceed user expectations in terms of reliability, accuracy, and usability.
- Trust and Credibility: Foster confidence among users, stakeholders, and society by ensuring ethical and transparent operation of the AI system

# Actions

- Evaluation of outputs is important as a safeguard for the system. Prevent inappropriate responses.




Validation and verifications | Change management | Configuration management | Risk management

Risk management is important and mechanisms are needed to assess data that cannot be clearly judged as inappropriate

Evaluation of Data

# Procedure and checkpoint

AISI Japan AI Safety Institute

Procedure

**Evaluation of data**

1. Prepare the evaluation data
2. Confirme with reliable data
3. Remove inappropriate responses based on evaluation data
4. Create error reports
5. Provide feedback to data owners
6. Provide feedback to system owners

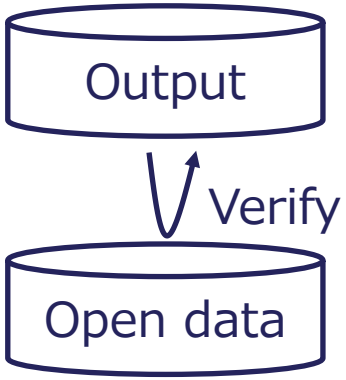
Checkpoint

- Are safeguards in place to prevent unethical responses?
- If a decision needs to be made on a response, does the process involve human intervention?
- Do you have mechanisms in place to investigate the causes of inappropriate responses and provide feedback?
- Are any outputs being produced that do not match the reliable data?

# Column: ASOT

- The **authoritative Source Of Truth** (ASOT) refers to the definitive, trusted source of information for a specific system, process, or context. It is the location where accurate, up-to-date, and complete data is maintained, ensuring consistency and reliability across systems or teams that rely on that information.

- By verifying using ASOT data, you can eliminate incorrect data and improve data quality. Open data provided by the government is a social infrastructure necessary for improving data quality.



# 7. Deliver the result

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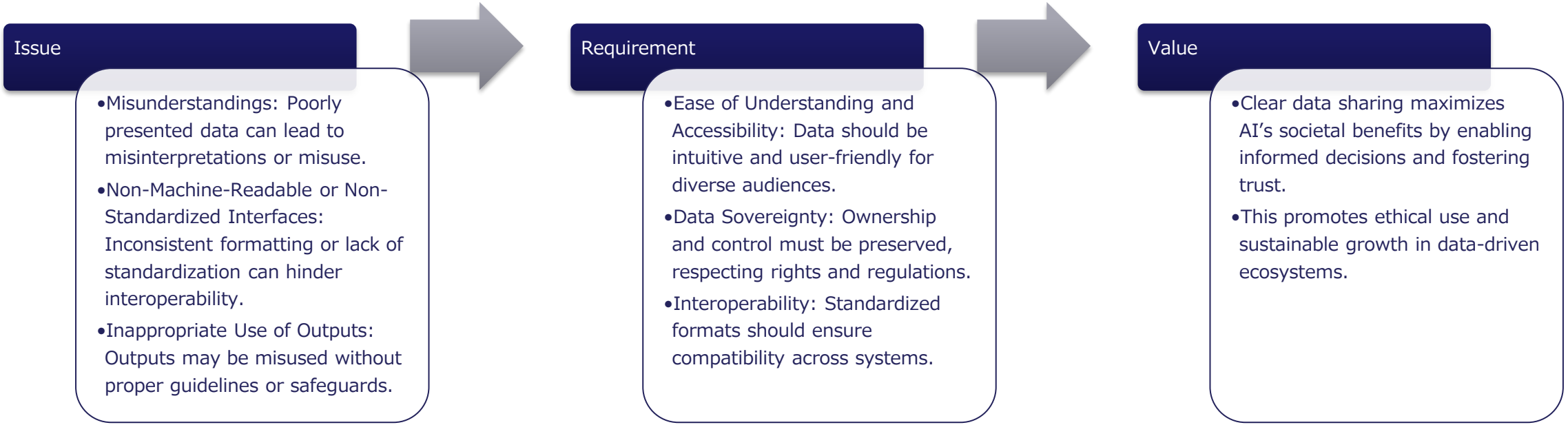
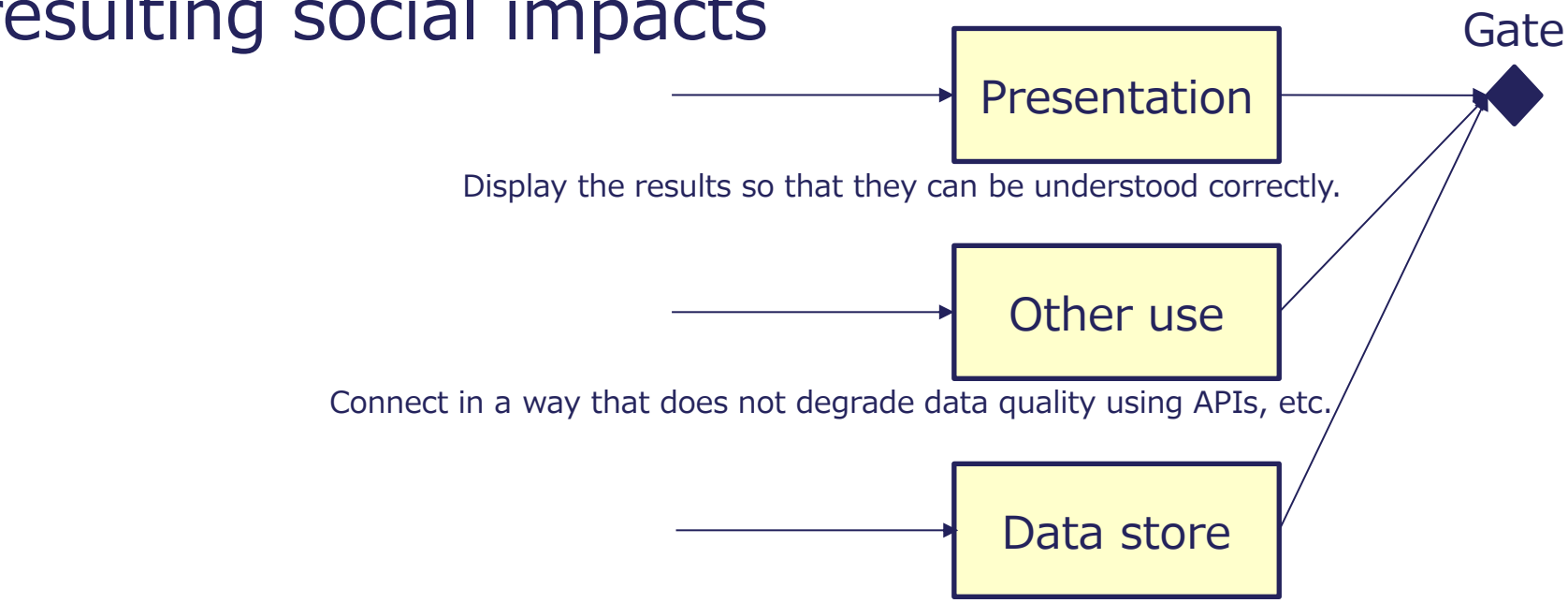
## Description

- This phase involves delivering processed data and AI outputs to end-users in a clear and accessible manner.
- Proper presentation prevents misunderstandings, ensuring trust and usability.
- Metadata adds clarity by providing context and reliability.
- Watermarking may also be used to secure data and protect intellectual property.



# Actions

- Outputs should be made publicly available or output for use in other systems. It is necessary to prevent misinterpretation and the resulting social impacts




Risk management is important and mechanisms are needed to assess data that cannot be clearly judged as inappropriate

Deliver the result

# Procedure and checkpoint

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| Procedure | Checkpoint |
| --- | --- |
| **Presentation**<br>1. Operate the access control function<br>2. Show the processing results<br>•Easy to understand<br>•Visualisation<br>3. Gather the user's opinion | ☐ Are the answers and expressions misleading?<br>☐ Is there a mechanism to check the basis of the answers, for example, by making the provincial information available for checking? |
| **4. Other use**<br>5. Operate the access control function<br>6. Provide API and relevant information | ☐ Does it provide a machine-readable interface? |
| **7. Data store**<br>8. Store the processing results<br>9. Backup the data<br>10. Optimize the data strage | ☐ Are protective actions taken to ensure that data is not lost? |

# Column: Social and human impact

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- Due to poor data quality, the system may provide incorrect data, which may shock or disadvantage users.
- Furthermore, due to poor data quality, it is possible that the system will provide incorrect data, which could lead to accidents or have an impact on the economy.

- In addition to assessing data before it is provided, it is also necessary to prepare countermeasures in the event of an impact.

# 8. Decommissioning

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## Description

- The data quality control process is finalized, and the data is officially decommissioned.
- Measures are taken to ensure that it is clearly marked as decommissioned to prevent accidental or unintended use.
- This step is critical to maintaining the integrity of AI systems and avoiding errors caused by outdated data.

**Issue**

- some users may unknowingly utilize decommissioned or outdated data, leading to inappropriate conclusions or results.

**Requirement**

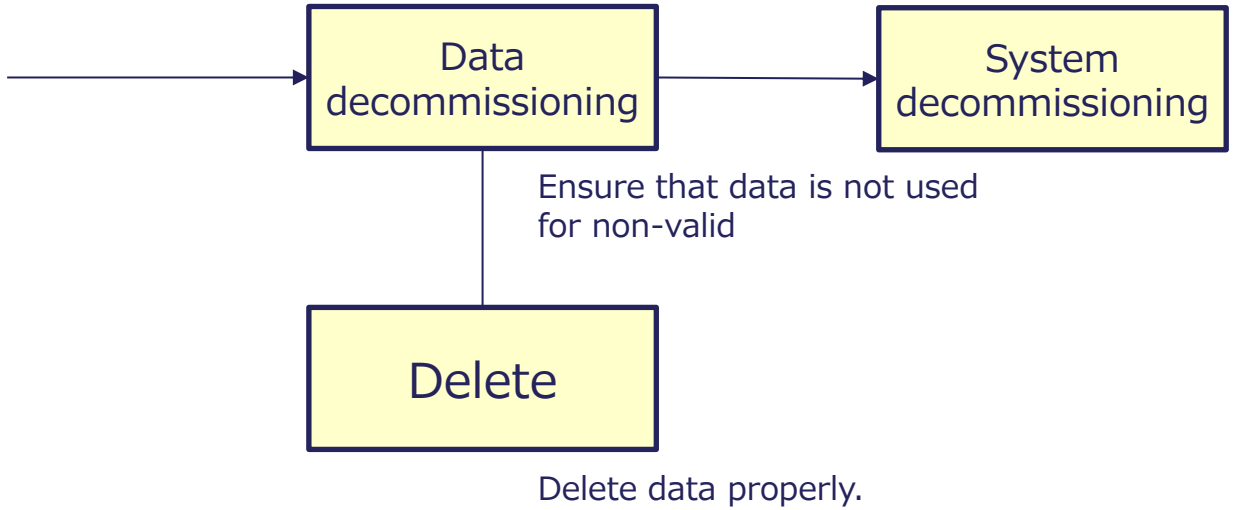
- It is essential to implement systems and processes that prominently notify users that the data has been decommissioned.
- This can include metadata updates, automated alerts, and clear documentation to ensure no ambiguity remains about the data's status.

**Value**

- By clearly marking and communicating decommissioned data, errors from outdated data use are minimized.
- This helps maintain AI system reliability and trust. It also boosts efficiency by reducing rework and supports better data governance practices.

# Actions

- Stop providing data. Advance notice of decommision and notice that the data is no longer guaranteed thereafter.




Validation and verifications | Change management | Configuration management | Risk management

Avoiding the risk of external service outages due to data no longer being supplied and the risk of outdated or unmodified information being used.

Data decommissioning

# Procedure and checkpoint

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| Procedure | Checkpoint |
| --- | --- |
| **Data decommissioning**<br>1. Notify users of the decommisioning of the service<br>2. Provides information on data that has been decommissioned.<br>3. When transferring data, the data, metadata and related documents are transferred. | ☐ Did you give sufficient notice before suspending the service?<br>☐ If you are transferring to another party, did you provide sufficient information for them to take over? |
| **Delete**<br>1. If necessary, archive the data.<br>2. Erase the data so that it cannot be restored<br>3. When deleting parts, you will give prior notice. | ☐ Did you check the results of the deletion? |

# 8. Action throughout the life cycle

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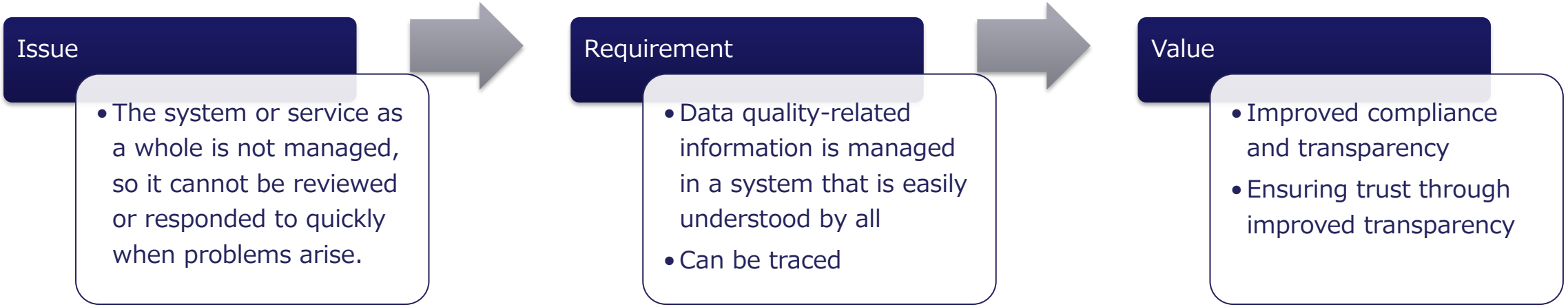
## Description

- It is necessary to implement ‘validation and verification’, ‘change management’, ‘configuration management’ and ‘risk management’ throughout the data lifecycle.
- Through these initiatives, we will improve data quality across processes.



Action throughout the life cycle

# Procedure and checkpoint

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| Procedure | Checkpoint |
| --- | --- |
| **Validation and verification**<br>1. Define the characteristics, targets and tolerance levels required for the system's purpose<br>2. Manage throughout the lifecycle | ☐ Is data quality control becoming a burden? |
| **Change management**<br>1. Define a basic policy for changes, such as data integration, processing and modification<br>2. Define policies for data degradation over time, e.g. data refreshing<br>3. Record changes | ☐ Is the change history readily available? |

Action throughout the life cycle

# Procedure and checkpoint

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| Procedure | Checkpoint |
| --- | --- |
| **Configuration management**<br>1. Manage software configuration<br>2. Manage data configurations<br>3. Manage the configuration of relevant documents | ☐ Do you manage the list of software, data and documents? |
| **Risk management**<br>1. Define data quality risks and response policies<br>2. Manage data risks through access control and continuous monitoring<br>3. Ensure that essential risk factors are addressed<br>4. Develop Business Continuity Plan (BCP) | ☐ Do you understand the risk of your system or service?<br>☐ When a risk is discovered, is there a culture in your organization that reviews the situation from the root cause? |

# Column: Access control

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- Access control is crucial for maintaining data quality by preventing data poisoning and other forms of unauthorized manipulation.
- By defining and regulating which users, devices, or processes have permission to access, modify, or delete data, organizations can significantly reduce the risk of malicious attacks and accidental errors.
- Key elements of effective access control include implementing clearly defined user roles and privileges, enforcing multi-factor authentication, regularly auditing access logs, and continuously monitoring for unusual or unauthorized activities.
- This structured approach ensures data remains accurate, consistent, and secure over its entire lifecycle.

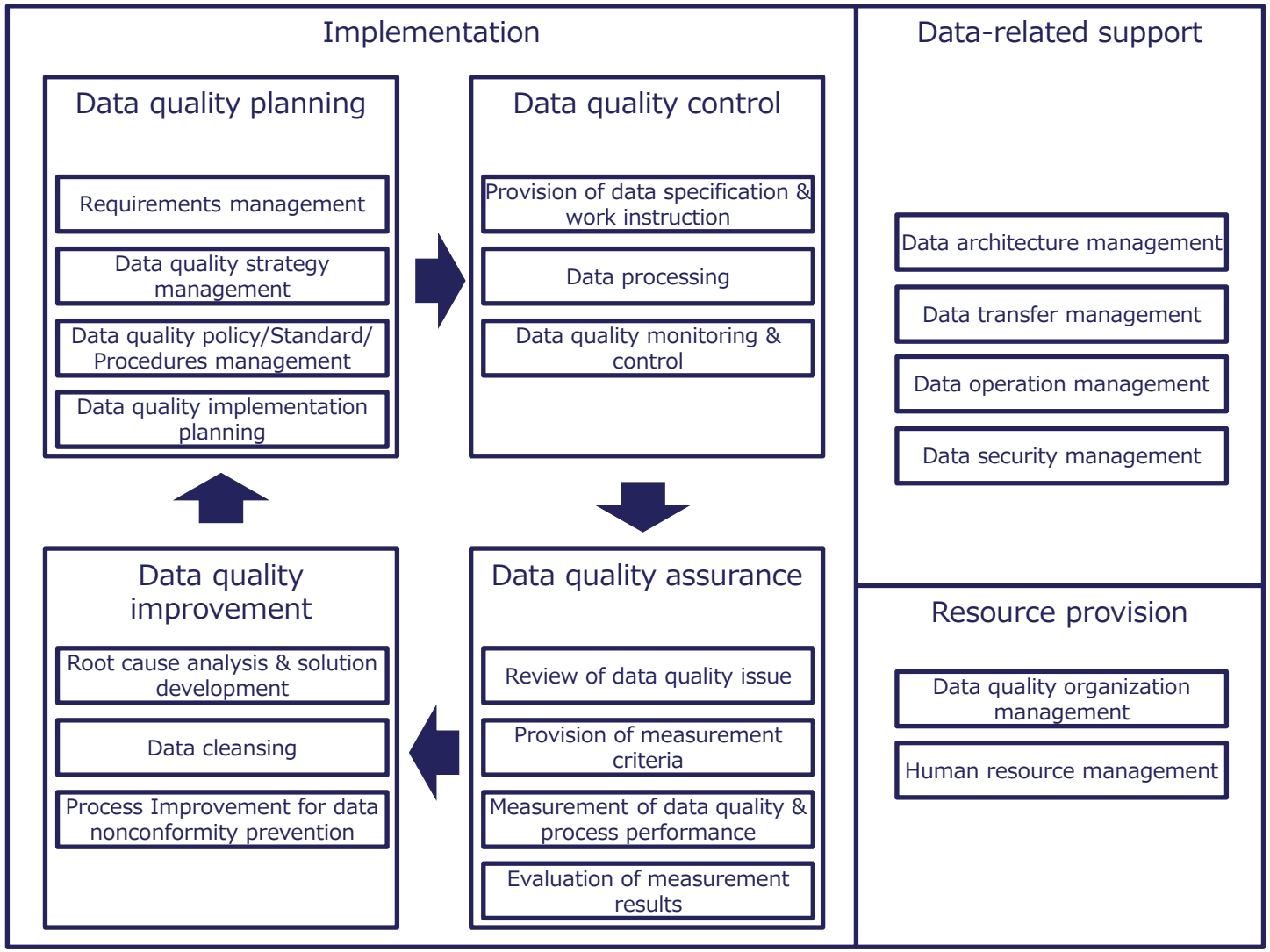
# Implementation

- Governance

# Governance cycle

Managing data quality involves getting individual activities right, as well as organisational controls to ensure they are sustainable and run smoothly.

Data governance in accordance with ISO 8000-61.



# Data quality planning

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- Data quality planning is essential for ensuring that AI systems are built on accurate, reliable, and consistent data.
- High-quality data enables AI models to perform effectively and ethically, reducing the risks of bias, errors, and poor decision-making.
- The process involves a structured approach to identify data requirements, define quality standards, establish policies, and implement actionable plans to manage data quality throughout the AI lifecycle.

# Data quality planning

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## Requirements

- Identify Business Needs Determine the specific objectives of the AI system and the data needed to achieve them.
- Define Data Quality Dimensions Establish the critical dimensions (e.g., accuracy, completeness, consistency, timeliness) relevant to the project.
- Assess Current Data Conduct a gap analysis of existing data to identify areas needing improvement.
- Document Requirements Clearly document the data quality requirements to guide subsequent processes.

## Data Quality Strategy

- Develop a Vision Define the long-term goals for data quality aligned with the AI system's objectives.
- Set Measurable Targets Establish key performance indicators (KPIs) to evaluate data quality over time.
- Stakeholder Engagement Ensure alignment with all stakeholders, including data engineers, analysts, and decision-makers.
- Risk Management Identify and mitigate potential risks associated with poor data quality in AI applications.

## Data Quality Policy/Standards/Procedures

- Define Policies Establish organizational policies for data governance and quality management.
- Create Standards Develop specific standards for data collection, storage, processing, and validation to ensure consistency.
- Document Procedures Outline detailed procedures for maintaining and improving data quality, such as periodic audits and validation protocols.
- Compliance Check Ensure that all policies and standards align with relevant legal and regulatory requirements.

## Data Quality Implementation Planning

- Develop an Action Plan Create a step-by-step plan for implementing data quality measures, including timelines and responsibilities.
- Assign Roles Define clear roles and responsibilities for team members involved in data quality management.
- Implement Tools and Processes Deploy tools for data cleansing, validation, monitoring, and reporting.
- Monitor and Refine Continuously monitor data quality and refine the implementation plan as needed based on feedback and performance metrics.

# Data quality control

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- Data quality control ensures that the data used in AI systems is accurate, consistent, and reliable.
- This process is critical for optimizing AI performance, reducing biases, and achieving trustworthy results.
- Effective data quality control involves clear specifications, robust processing techniques, and continuous monitoring to identify and resolve quality issues.

# Data quality control

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## Provision of Data Specifications and Work Instructions

- Define clear data requirements, including formats, structures, and acceptable value ranges.
- Provide detailed instructions for data collection, labeling, and processing to ensure uniformity.
- Establish guidelines for metadata creation to track data sources, timestamps, and contextual information.
- Develop a validation checklist for contributors to ensure adherence to data quality standards.

## Data Processing

- Clean and preprocess data to remove inconsistencies, duplicates, and irrelevant information.
- Normalize data to ensure compatibility across systems (e.g., format conversions, scaling).
- Annotate and label data accurately for supervised learning models.
- Implement automated data validation tools to identify anomalies and errors during processing.
- Document every processing step to maintain traceability and reproducibility.

## Data Quality Monitoring and Control

- Establish key quality metrics (e.g., accuracy, completeness, consistency, timeliness).
- Implement real-time monitoring systems to detect data quality issues promptly.
- Schedule regular data audits to review and validate data integrity.
- Use AI tools to identify patterns of errors or potential biases in datasets.
- Create feedback loops to continuously improve data quality standards based on findings.

# Data quality assurance

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- Data quality assurance (DQA) ensures that the data used in AI development and operations meets the necessary standards of accuracy, consistency, completeness, and reliability.
- This process is critical to avoid errors, biases, and inefficiencies in AI systems.
- DQA involves identifying potential data quality issues, establishing criteria for evaluation, measuring data quality, and analyzing results to guide improvements.

# Data quality assurance

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## Review of Data Quality Issues

- Identify potential issues such as missing values, inconsistencies, inaccuracies, or redundancies in the dataset.
- Analyze root causes of data quality problems, including errors in data collection, processing, or storage.
- Document known issues and assess their potential impact on AI model performance.

## Provision of Measurement Criteria

- Define clear and measurable criteria for data quality attributes (e.g., accuracy, completeness, timeliness, consistency, and validity).
- Establish benchmarks and thresholds that data must meet to be considered suitable for use.
- Align criteria with the specific requirements of AI models and business objectives.

## Measurement of Data Quality and Process Performance

- Conduct systematic evaluations of datasets against the established measurement criteria.
- Use data profiling tools to detect anomalies and assess quality attributes.
- Monitor data processing workflows to ensure consistent adherence to quality standards.

## Evaluation of Measurement Results

- Analyze measurement outcomes to identify gaps and areas for improvement.
- Quantify the impact of data quality issues on AI system performance and decision-making.
- Generate reports and dashboards to communicate findings to stakeholders.

# Data quality improvement

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- Data quality improvement is a critical process to ensure the reliability and effectiveness of AI systems.
- It involves identifying and resolving data issues, enhancing data consistency, and establishing preventive measures to maintain high-quality data over time.
- This process ensures that AI models can deliver accurate, unbiased, and actionable insights.

# Data quality improvement

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## Root Cause Analysis and Solution Development

- Identify the Source of Issues: Investigate the underlying causes of data quality problems, such as incorrect data entry, system errors, or outdated data.
- Develop Targeted Solutions: Design and implement specific corrective actions to address identified root causes, such as updating workflows, improving validation rules, or automating data entry processes.
- Monitor and Validate Results: Continuously evaluate the effectiveness of implemented solutions to ensure the issues are resolved and do not reoccur.

## Data Cleansing

- Identify Inaccuracies: Detect duplicate, incomplete, or inconsistent records within the dataset.
- Standardize Data Formats: Ensure uniformity in data presentation, such as consistent date formats, unit measurements, and naming conventions.
- Correct or Remove Errors: Modify inaccurate entries, fill missing values, or remove irrelevant or outdated data to maintain dataset integrity.
- Automate Cleansing Processes: Leverage tools and algorithms to automate repetitive data cleansing tasks and reduce manual errors.

## Process Improvement for Data Nonconformity Prevention

- Establish Data Governance Policies: Define and enforce clear policies for data collection, management, and usage to prevent quality issues.
- Enhance Data Validation Mechanisms: Implement real-time validation checks during data entry or ingestion to identify nonconformities early.
- Train Stakeholders: Educate employees and data handlers about best practices for maintaining data quality and the importance of adhering to standards.
- Monitor and Audit Data Processes: Regularly assess data workflows to detect potential sources of nonconformity and ensure compliance with established policies.

# Data-related support

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- Effective data quality governance is critical for AI development and utilization.
- Data-related support encompasses a comprehensive set of activities designed to ensure the integrity, consistency, and reliability of data across its lifecycle.
- These efforts focus on establishing frameworks, processes, and tools to optimize data management while addressing compliance, security, and operational needs.

# Data-related support

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## Data Architecture Management

- Define data models, schemas, and standards to ensure consistency. Develop and manage metadata repositories to enhance data discoverability and traceability.
- Implement data lineage tracking to monitor the flow and transformation of data.
- Ensure scalability and flexibility to accommodate evolving AI demands.
- Align architecture with organizational goals and compliance requirements.

## Data Transfer Management

- Establish protocols for secure data transfer (e.g., encryption, VPNs).
- Monitor and optimize data flow to prevent bottlenecks and ensure real-time availability. Maintain logs and audits of data transfers for accountability and traceability.
- Define policies for cross-border data transfers to comply with legal regulations (e.g., GDPR, CCPA).
- Automate data transfer processes where applicable to reduce manual errors.

## Data Operations Management

- Conduct regular data validation and cleansing to maintain accuracy.
- Manage data storage solutions to ensure accessibility and scalability.
- Establish workflows for data ingestion, processing, and integration. Monitor system performance and resolve issues related to data operations.
- Implement version control for datasets to track changes and ensure consistency.

## Data Security Management

- Implement access controls, including role-based permissions and multifactor authentication.
- Conduct regular security audits and vulnerability assessments.
- Deploy encryption protocols for data at rest and in transit. Monitor for suspicious activities and respond to security incidents promptly.
- Ensure compliance with global and local data protection regulations.

# Resource provision

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- Resource provision supports effective data quality governance by ensuring that the necessary organizational structures, human resources, and operational capabilities are in place.
- This ensures high-quality data for AI systems, minimizing risks and maximizing the accuracy, reliability, and fairness of AI models.
- The process involves structuring teams, allocating skilled personnel, and defining clear roles and responsibilities.

# Resource provision

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## Data Quality Organization Management

- Establishing a dedicated Data Quality Governance team or council.
- Defining roles and responsibilities for data quality management (e.g., Data Stewards, Data Quality Analysts).
- Setting up clear reporting lines and accountability for data quality issues.
- Creating cross-functional collaboration frameworks to involve stakeholders from various departments.
- Regularly reviewing and updating organizational structures to adapt to evolving data and AI needs.

## Human Resource Management

- Recruiting data quality professionals with expertise in data governance, data architecture, and AI integration.
- Providing training programs to enhance employees' skills in data quality assessment, cleansing, and validation.
- Defining career paths and development plans for data governance professionals to improve retention.
- Ensuring adequate staffing levels for ongoing data quality monitoring and improvement tasks.
- Promoting a culture of data quality awareness and accountability across the organization.

# Implementation

- Characteristics

# Verification of data quality characteristics.

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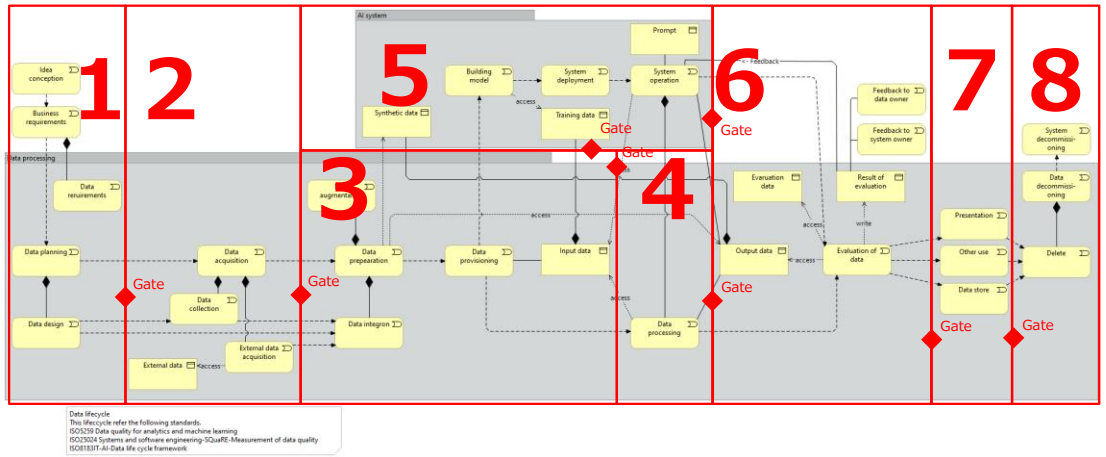
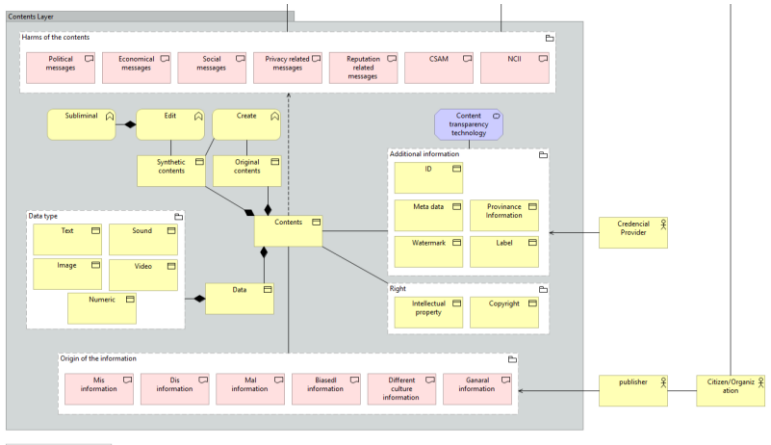
- To maintain data quality, data quality needs to be checked at process boundaries and transactions.
- In the case of sensor data, this may be a periodic inspection.
- During the inspection process, each characteristic should be checked, assuming the type of data and events that may degrade the quality of the data.
- The checking of characteristics should be automated where possible, so as not to increase the workload on the site.



# List of characteristics

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- Utilises the required quality characteristics from amongst many characteristics.

**Inherent data quality characteristics**

- Accuracy
- Completeness
- Consistency
- Credibility
- Currentness

**Inherent and system-dependent data quality characteristics**

- Accessibility
- Compliance
- Confidentiality
- Efficiency
- Precision
- Traceability
- Understandability

**System-dependent data quality**

- Availability
- Portability
- Recoverability

**Additional data quality characteristics**

- Auditability
- Balance
- Diversity
- Effectiveness
- Identifiability
- Relevance
- Representativeness
- Similarity
- Timeliness

**Sensor data quality characteristics**

- Accuracy
- Completeness
- Consistency
- Precision

# Inherent data quality characteristics

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## Accuracy

- Accuracy ensures the data reflects real-world values correctly. High accuracy is vital for AI to produce reliable outcomes, avoiding false predictions or flawed decisions.

- Evaluation Points
  - Data matches verified sources.
  - Error rate is within acceptable thresholds.
  - Outliers are justified or corrected.
- Inappropriate Examples
  - Incorrect labels in training datasets.
  - Mismatched units in numerical data.
  - Spelling errors in text data.

# Inherent data quality characteristics

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## Completeness

- Completeness measures if all required data points are present. Missing values can distort AI predictions and compromise system effectiveness.

- Evaluation Points
  - All critical fields are filled.
  - Null or missing rates are minimal.
  - Completeness checks align with AI model requirements.
- Inappropriate Examples
  - Missing demographic attributes in user profiles.
  - Partial transaction records.
  - Null values in key input variables.

# Inherent data quality characteristics

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## Consistency

- Consistency ensures data values are uniform across datasets and time. Inconsistencies can cause AI to misinterpret patterns.

- Evaluation Points
  - Uniform formatting and units.
  - Synchronized datasets over time.
  - No conflicting entries within linked data.
- Inappropriate Examples
  - Different date formats in a dataset.
  - Duplicate records with conflicting details.
  - Mismatched entries in integrated datasets.

# Inherent data quality characteristics

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## Credibility

- Credibility measures the trustworthiness of data sources. Reliable sources improve AI model validity and trust.

- Evaluation Points
  - Verified, reputable data origins.
  - Data provenance is documented.
  - Peer-reviewed or authenticated sources.
- Inappropriate Examples
  - Data from unknown/unverified sources.
  - Fake or manipulated datasets.
  - User-generated content without validation.

# Inherent data quality characteristics

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## Currentness

- Currentness assesses how up-to-date data is. Stale data can result in outdated AI insights or actions.

- Evaluation Points
  - Data aligns with the latest context.
  - Timestamping practices ensure traceability.
  - Regular updates are maintained.
- Inappropriate Examples
  - Outdated stock prices in financial models.
  - Old weather data in climate predictions.
  - Historical user preferences in real-time applications.

# Inherent and system-dependent data quality characteristics

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## Accessibility

- Accessibility ensures data is available to authorized users and systems without barriers. It involves proper storage, robust APIs, and universal design principles for all users. Accessibility supports efficient AI model training and application by enabling smooth data flow.

- Evaluation Points
  - Data can be accessed across platforms and devices.
  - APIs are well-documented and error-free.
  - Meets accessibility standards for all user demographics.
- Inappropriate Examples
  - Data locked in proprietary formats.
  - Missing API documentation.
  - Non-compliance with ADA accessibility standards.

# Inherent and system-dependent data quality characteristics

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## Compliance

- Compliance refers to ensuring data management adheres to laws, regulations, and industry standards like GDPR or CCPA. Proper compliance avoids legal risks, protects privacy, and builds trust, critical for AI system reliability and public acceptance.

- Evaluation Points
  - Meets all relevant legal standards.
  - Implements proper data consent mechanisms.
  - Regular compliance audits conducted.
- Inappropriate Examples
  - Collecting data without consent.
  - Ignoring jurisdictional privacy laws.
  - Lacking audit trails for data handling.

# Inherent and system-dependent data quality characteristics

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## Confidentiality

- Confidentiality ensures sensitive data is protected from unauthorized access or breaches. Encryption, access controls, and anonymization techniques are critical. Maintaining confidentiality safeguards trust and minimizes risks associated with data misuse.

- Evaluation Points
  - Strong encryption for data at rest and transit.
  - Role-based access control systems.
  - Regularly updated security protocols.
- Inappropriate Examples
  - Storing sensitive data in plaintext.
  - Sharing private data without consent.
  - Weak or outdated access controls.

# Inherent and system-dependent data quality characteristics

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## Efficiency

- Efficiency in data management minimizes processing time and resource usage without compromising quality. Efficient data ensures faster AI training and deployment, cost savings, and scalability.

- Evaluation Points
  - Optimized data storage structures.
  - Minimal latency in data access.
  - Efficient ETL pipelines.
- Inappropriate Examples
  - Redundant data processing steps.
  - High latency in API calls.
  - Excessive resource consumption for simple tasks.

# Inherent and system-dependent data quality characteristics

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## Precision

- Precision ensures data accuracy and correctness, reducing errors in AI training and predictions. High precision relies on rigorous validation, consistent data formats, and minimal ambiguity.

- Evaluation Points
  - Data aligns with source truth.
  - Strict validation rules applied.
  - Consistent units and formats.
- Inappropriate Examples
  - Inconsistent data formats.
  - Incorrect data entries.
  - Ambiguity in source data interpretation.

# Inherent and system-dependent data quality characteristics

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## Traceability

- Traceability tracks the origin, transformations, and use of data, ensuring accountability and reproducibility. Detailed logs and metadata enhance transparency, critical for debugging and compliance.

- Evaluation Points
  - Comprehensive data lineage documentation.
  - Transformation logs maintained.
  - Unique IDs for traceability.
- Inappropriate Examples
  - Missing source details for datasets.
  - Unlogged data modifications.
  - Inconsistent versioning of datasets.

# Inherent and system-dependent data quality characteristics

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## Understandability

- Understandability ensures data can be interpreted correctly by both humans and machines. Clear labeling, metadata, and intuitive structures improve usability, essential for effective AI training.

- Evaluation Points
  - Data labeled clearly and comprehensively.
  - Metadata aligns with schema standards.
  - Consistent and logical data structure.
- Inappropriate Examples
  - Vague or missing labels.
  - Complex, undocumented structures.
  - Misleading metadata annotations.

# System-dependent data quality

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## Availability

- Availability ensures that AI data is accessible whenever needed. Reliable systems minimize downtime and ensure continuous operation, crucial for real-time AI applications.

- Evaluation Points
  - Uptime percentage meets service-level agreements (SLAs).
  - Redundancy mechanisms to prevent single points of failure.
  - Regular monitoring and alerts for accessibility issues.
- Inappropriate Examples
  - Frequent server outages disrupting data access.
  - No backups, leading to inaccessible data during hardware failure.
  - Delays in resolving access issues during critical tasks.

# System-dependent data quality

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## Portability

- Portability refers to the ability to transfer AI data seamlessly across platforms, systems, or environments without compatibility issues. It ensures flexibility and adaptability.

- Evaluation Points
  - Data is stored in widely accepted formats (e.g., CSV, JSON).
  - Use of standardized APIs for data exchange.
  - Adequate documentation for data migration.
- Inappropriate Examples
  - Proprietary formats requiring specialized software.
  - Inconsistent data structures across systems.
  - Lack of metadata, causing misinterpretation during migration.

# System-dependent data quality

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## Recoverability

- Recoverability focuses on the system's ability to restore AI data quickly and accurately after unexpected disruptions or failures, ensuring minimal data loss.

- Evaluation Points
  - Regular backups with multiple restore points.
  - Disaster recovery plans tested periodically.
  - Redundant storage to avoid single points of failure.
- Inappropriate Examples
  - Outdated backups causing irreversible data loss.
  - Recovery processes requiring significant manual intervention.
  - Failure to test recovery plans, leading to delays.

# Additional data quality characteristics

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## Auditability

- Auditability ensures data traceability and the ability to review the process of data collection and usage. It enables accountability and compliance with ethical and legal standards.

- Evaluation Points
  - Clear documentation of data sources.
  - Well-defined data collection processes.
  - Availability of data lineage records.
- Inappropriate Examples
  - Missing metadata for data sources.
  - Ambiguous data provenance.
  - Inaccessible logs for key data processes.

# Additional data quality characteristics

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## Balance

- Balance ensures data represents all relevant categories or outcomes proportionally, minimizing bias in AI models.

- Evaluation Points
  - Equal representation of categories.
  - Avoidance of over/under-sampling.
  - Consistency across datasets.
- Inappropriate Examples
  - Gender imbalance in a dataset.
  - Skewed representation of geographical regions.
  - Over-representation of one age group.

# Additional data quality characteristics

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## Diversity

- Diversity ensures datasets include a wide range of perspectives, scenarios, and variations for better generalization in AI systems.

- Evaluation Points
  - Coverage of different cultural contexts.
  - Inclusion of varied scenarios and demographics.
  - Range of linguistic expressions.
- Inappropriate Examples
  - Excluding minority dialects.
  - Homogenous data in multilingual settings.
  - Ignoring varied environmental factors.

# Additional data quality characteristics

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## Effectiveness

- Effectiveness measures whether the data fulfills its intended purpose and supports the desired model outcomes.

- Evaluation Points
  - Alignment with model objectives.
  - Testing for model improvements.
  - Appropriate feature representation.
- Inappropriate Examples
  - Redundant data with no value.
  - Data leading to incorrect predictions.
  - Irrelevant features lowering model performance.

# Additional data quality characteristics

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## Identifiability

- Identifiability ensures that sensitive or personal data is anonymized to protect privacy while maintaining utility.

- Evaluation Points
  - Adherence to anonymization standards.
  - Removal of personal identifiers.
  - Assessment of re-identification risks.
- Inappropriate Examples
  - Retention of identifiable personal details.
  - Incomplete data masking.
  - Reversible pseudonymization techniques.

# Additional data quality characteristics

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## Relevance

- Relevance ensures data aligns with the use case, covering only necessary and meaningful information.

- Evaluation Points
  - Targeted data for the AI model's domain.
  - Exclusion of irrelevant variables.
  - Avoidance of redundant information.
- Inappropriate Examples
  - Outdated information in dynamic applications.
  - Including unrelated features.
  - Excessive focus on non-critical variables.

# Additional data quality characteristics

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## Representativeness

- Representativeness ensures that data reflects the real-world population or scenarios the AI model will encounter.

- Evaluation Points
  - Alignment with target population characteristics.
  - Coverage of expected conditions.
  - Avoidance of sampling bias.
- Inappropriate Examples
  - Over-sampling urban populations in national studies.
  - Ignoring rare but critical conditions.
  - Incomplete geographic coverage.

# Additional data quality characteristics

AISI Japan AI Safety Institute

## Similarity

- Similarity measures the consistency between training and real-world data, reducing model performance gaps.

- Evaluation Points
  - Alignment with deployment environment.
  - Testing against real-world scenarios.
  - Identification of data mismatches.
- Inappropriate Examples
  - Synthetic data misrepresenting reality.
  - Inconsistent formatting across datasets.
  - Differences in distributions between datasets.

# Additional data quality characteristics

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- Timeliness
  - Timeliness ensures data is up-to-date and reflects current conditions, crucial for accuracy in dynamic models.

  - Evaluation Points
    - Regular data updates.
    - Tracking of time-sensitive variables.
    - Expiration checks on older datasets.
  - Inappropriate Examples
    - Using outdated population statistics.
    - Training on obsolete customer trends.
    - Neglecting updates in real-time applications.

# Characteristics of Sensor data

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- Although each piece of sensor data is small, when aggregated in real time, it can become a large amount of data.
- Many of them are incorporated into devices and services and are directly linked to safety. In addition, they are often set up in various environments, such as outdoors, and are easily affected by the external environment.
- On the other hand, when there are many sensors, if one fails, it can be supplemented using data from surrounding sensors, and in some cases, data can be supplemented using data from before and after in chronological order.
- For these reasons, the following four points need to be managed as particularly important data quality items.
  - Accuracy, Completeness, Consistency, Precision

# Time characteristics of sensor data

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- Sensor data may change over time and data characteristics may change, requiring compensation measures.

**Offset**
Constant deviation from true value.

**Drift**
Gradual change over time.

**Trim**
Adjustment to correct error.

**Spike**
Sudden, short-lived jump.

**Noise**
Random variations in data.

**Data loss**
Missing data points or gaps.

**Lack of amount**
Insufficient data collected.

**Shift**
Sudden baseline change.

**Drop or Rise**
Abrupt decrease or increase.

**Stuck**
Repeated constant readings.

**Bound oscillation**
Regular, limited fluctuations.

**Inconsistent frequency**
Irregular data intervals.

**Different resolution**
Varying data granularity.

**Incorrect timestamp**
Misaligned time in records.

**Latency**
Delay between event and record.

# Challenges in using multiple sensors

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When using multiple sensors, the following data quality issues can arise:

1. Inconsistent Data
   - Mismatch in Sensor Outputs: Different sensors measuring the same phenomenon might provide inconsistent values due to calibration errors or varying sensitivity.
   - Different Units or Scales: Sensors may report data in incompatible units or scales.
2. Temporal Misalignment
   - Clock Drift: Sensors might not be synchronized, causing timestamps to be out of alignment.
   - Latency Variability: Different sensors may have varying delays in recording or transmitting data.
3. Spatial Misalignment
   - Incorrect Sensor Positioning: Sensors may not be placed in the correct locations, leading to inaccurate measurements for a specific area or system.

# Challenges in using multiple sensors

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4. Noise and Interference
    - Environmental Noise: Sensors may pick up irrelevant signals from the environment, degrading the data quality.
    - Cross-Talk: Signals from one sensor interfere with another, causing erroneous readings.
5. Resolution and Precision Variability
    - Different Granularities: Sensors may record data at different levels of precision or resolution, making integration challenging.
    - Sampling Rate Disparities: Inconsistent sampling rates across sensors lead to incomplete or redundant data points.
6. Faults and Anomalies
    - Sensor Drift: Some sensors might degrade over time, resulting in inaccurate data.
    - Stuck or Frozen Sensors: Sensors might repeatedly report the same value due to hardware issues.
    - Data Gaps: Sensor failures or transmission errors lead to missing data.

# Challenges in using multiple sensors

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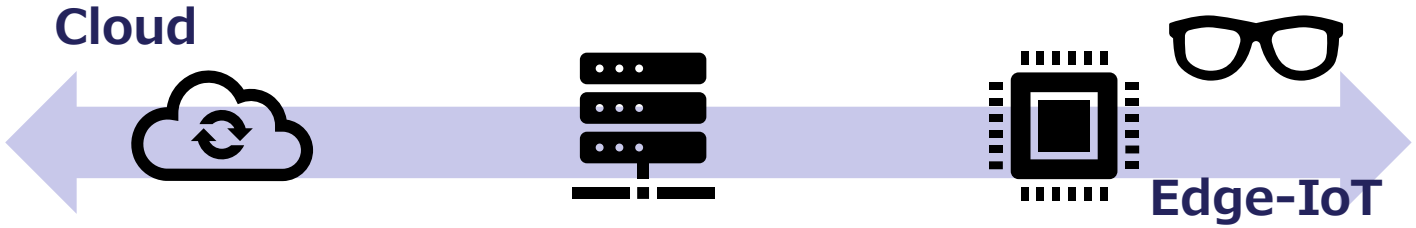
7. Redundancy and Overlap
    - Duplicate Data: Overlapping sensor coverage might lead to redundant data, increasing processing complexity.
    - Conflicting Data: Redundant sensors may report contradictory values.
8. Incorrect Calibration
    - Bias Errors: Calibration issues lead to consistent offsets or scaling errors in the measurements.
9. Integration Challenges
    - Different Protocols: Sensors using different communication protocols might make data integration difficult.
    - Heterogeneous Data Formats: Sensors may produce data in varied formats that need standardization.
10. Environmental Impact
    - Temperature, Humidity, or Pressure: Environmental conditions might affect sensor performance differently.

# Processing with Cloud-Edge-IoT

- Data collected by IoT devices and Edge may be processed on devices such as EdgeAI, at data aggregation points, or collected in the cloud for mass data processing, requiring data quality measures at each location.
  - Cloud: detects unusual or biased data in the course of processing large volumes of data.
  - Aggregation point: data is aggregated in areas. Data conversion and integration, if necessary; some instructions may be sent to EDGE.
  - Edge: At the Edge, data processing such as data cleansing, recognition and anonymisation processes are carried out. Corrections such as sensor-specific offsets may also be performed.

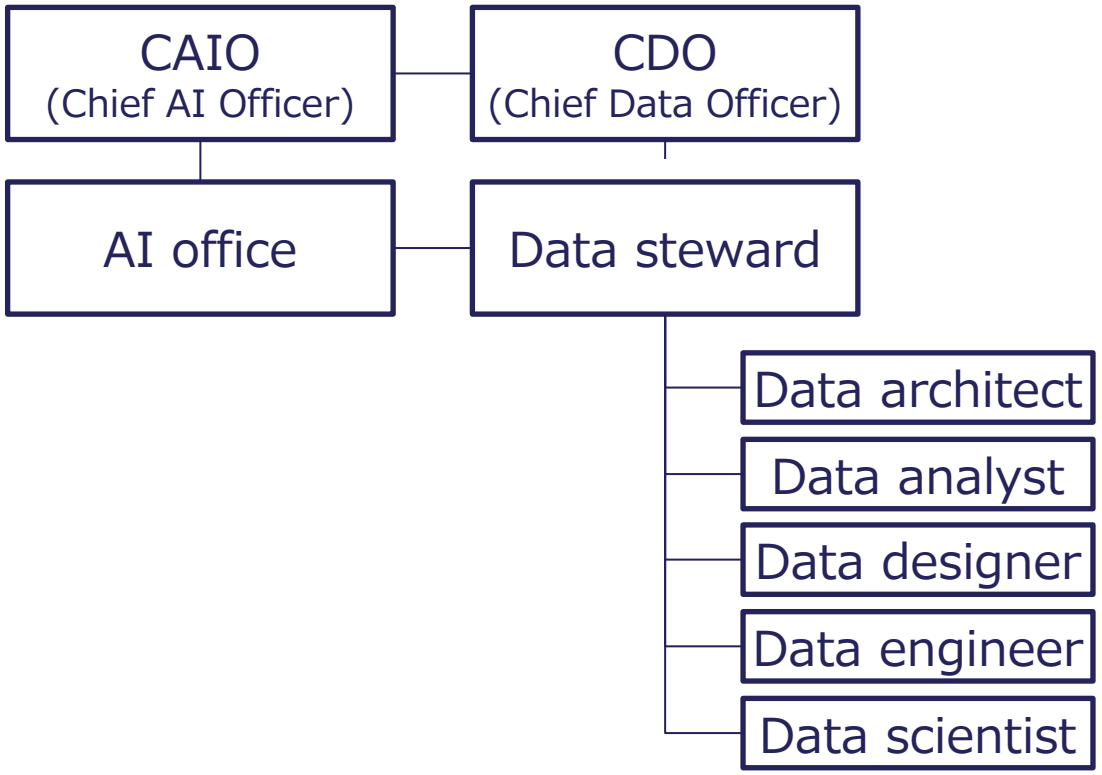


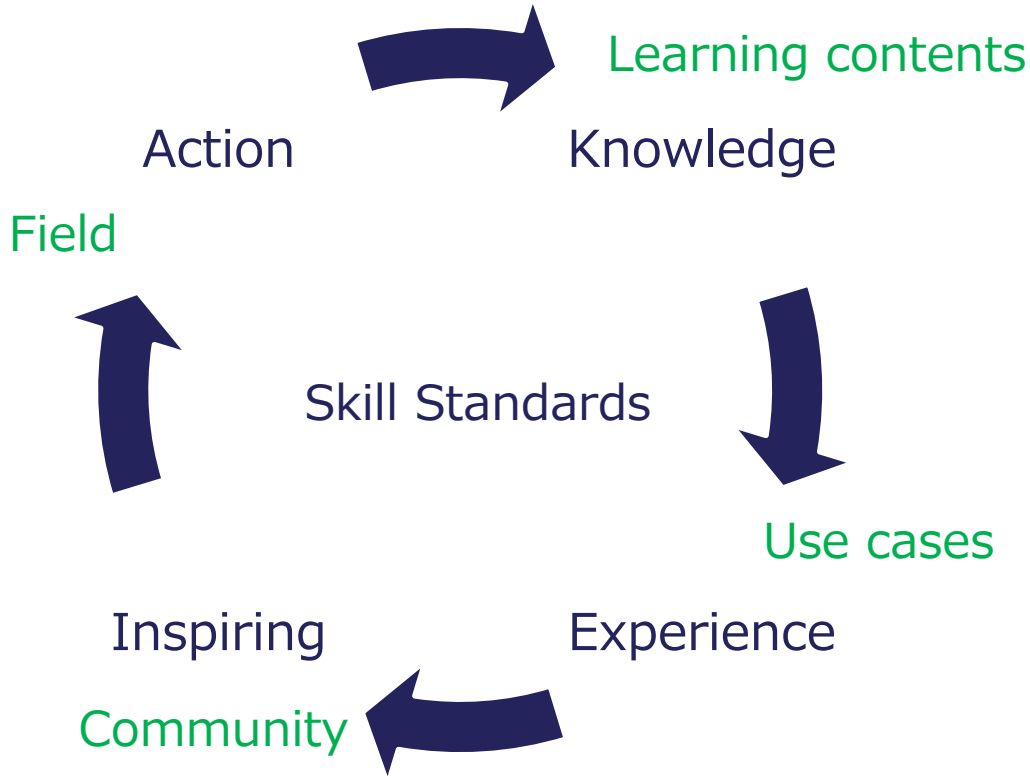
# Implementation

- Human resource and team

# Human resource and team

- The data governance team will work with the AI team to improve data quality.




- Business fields using the data also need literacy training, including on data quality.

# Postscript and other information

# Message

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- People are focusing on the cutting-edge technology of AI, but in order to ensure that we can use AI society in a sustainable and secure way, it is important to properly manage the quality of data.
- Keep in mind that “garbage in, garbage out” at all times, and let's make the most of the value of AI. ”

# About us and this document

AISI Japan AI Safety Institute

- AISI is the government initiative responsible for ensuring safety as a foundation for accelerating AI and AI-based innovation.
- IPA is a government funded organisation on digital technologies that participates in AISI's activities.

- This document has been jointly produced by AISI's standards team and a team of data experts from IPA's Digital Infrastructure Centre.
- It is currently in draft version. It will be released as an live version in March, based on domestic and international feedback.
- We look forward to hearing from you.

# References


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# Appendix

## Machine Learning Quality Management Guideline 4th Edition

Technical Report Artificial Intelligence Research Center
National Institute of Advanced Industrial Science and Technology (AIST)
2023-12-12

# Structure for achieving product quality

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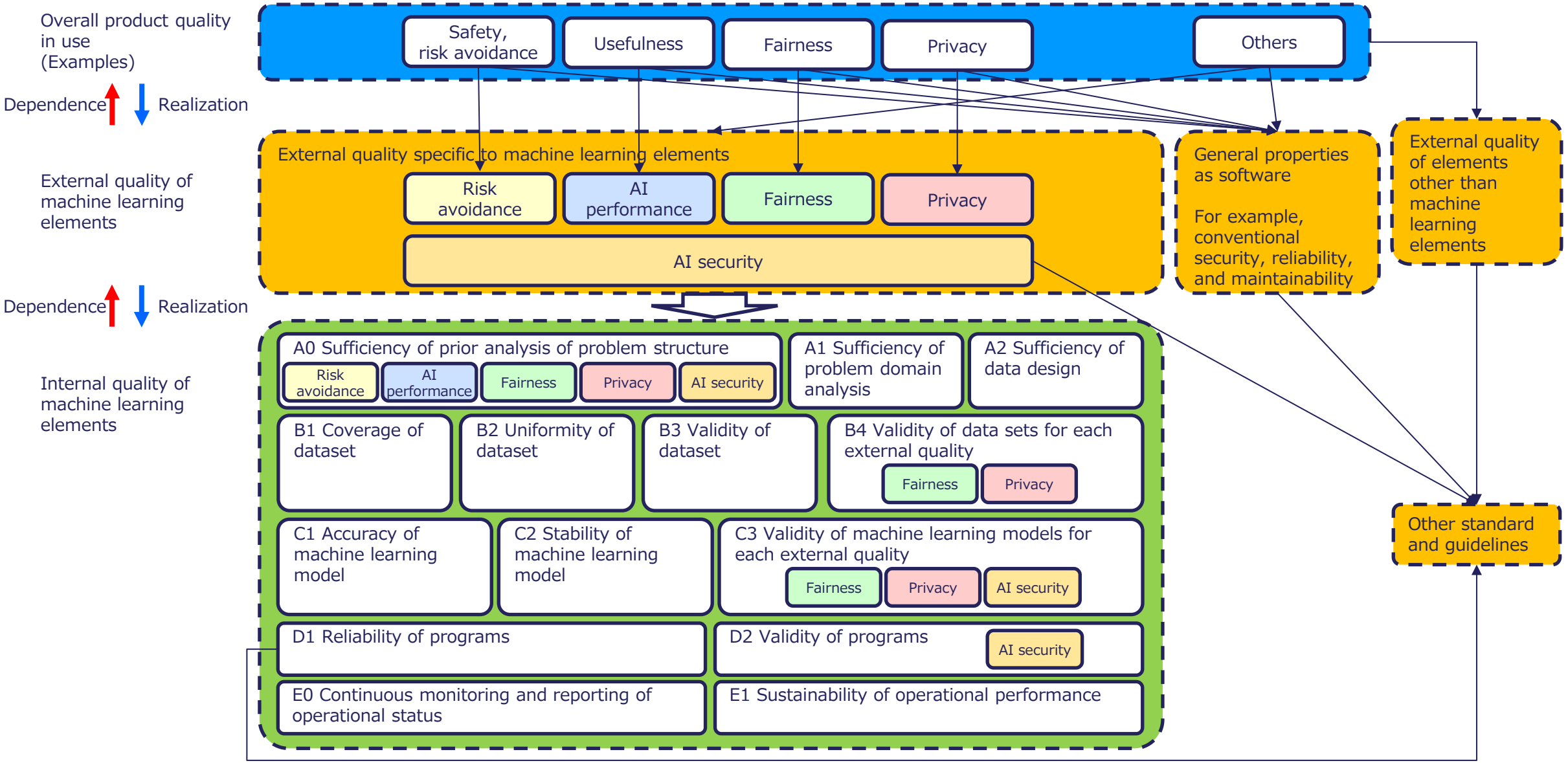

# Internal quality characteristics

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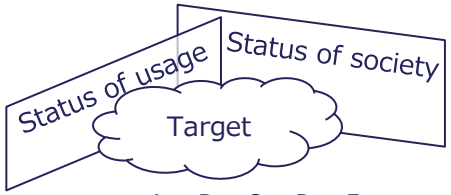
Data is a core element in AI. This guideline offers guidance on data quality management issues and responses to consider when promoting machine learning.

Analysis of issues

Data quality design

Data quality

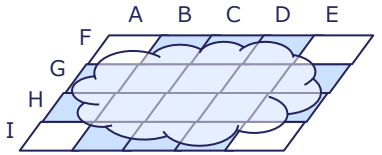
**A0 Sufficiency of prior analysis of problem structure**




Analyze the causes and structure of the issues that are the subject of quality

- Identify the causes and structure of usage and social conditions
- Organize by external quality characteristics
- Choose a position based on changes in trends

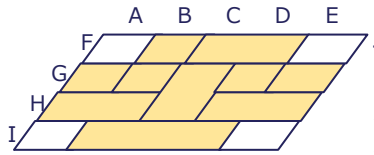
**A1 Sufficiency of problem domain analysis**




To determine operational input conditions of the ML component

- Identify expected range of inputs
- Provide a concrete notion of conditions e.g.using data-labels
- Distinguish between unsupported and rare conditions

**A2 Sufficiency of data design**



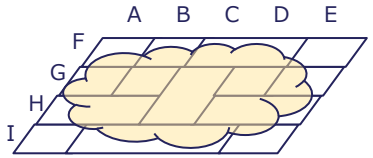

To identify combinations of conditions used for data quality management

- To Exaustivelycovers high-risk combinations of conditions
- To limit total numbers of combinations to tractive one

**B1 Coverage of dataset**

Compromise or Balancing needed

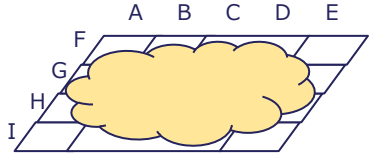
**B2 Uniformity of dataset**




To ensure that good data is available for each identified condition combinations

- Enough amount of data
- Unbiased data within each combinations

→ Ensuring good effort of training for important conditions

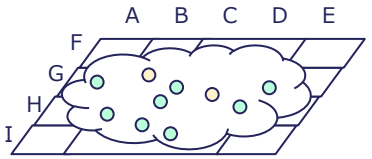



To ensure good distribution of data for the whole domain of input data

→ To achieve a model with good performance

**B3 Validity of dataset**

**B4 Validity of data sets for each external quality**




That each piece of data is valid

- Validity of measured values
- Validity of labels

Fairness | Privacy

Requirements for data sets that only relate to specific external quality

# Internal quality characteristics(Cont.)

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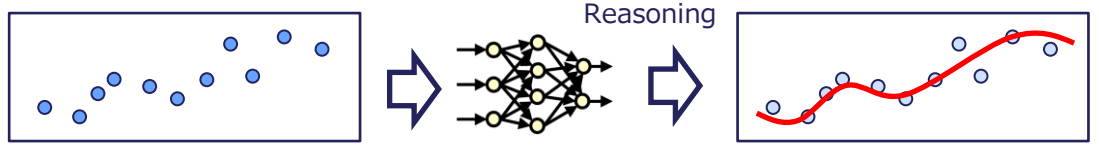
Quality of Machine learning model




C1 Accuracy of machine learning model

Good outputs on data points available in training/test dataset
- Directly evaluated by testing result

C2 Stability of machine learning model

Good, stable outputs on points not availablein training/test datasets
- Directly: by numerical analysis
- Indirectly: through test methods mgmt.

C3 Validity of machine learning models for each external quality

Fairness | Privacy | AI security

Requirements for machine learning models that only relate to specific external quality

Quality of implementation and operation

D1 Reliability of programs

Ensuring the quality of software other than the trained model

D2 Validity of programs

Addressing issues that cannot be handled by data and machine learning model management through programming

E0 Continuous monitoring and reporting of operational status

Recording operational status as evidence and for addressing issues and improving quality

E1 Sustainability of operational performance

Maintaining the quality secured after the start of operation during the operation period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