



NTNU

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The role of data in developing public services

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JRC SCIENCE FOR POLICY REPORT

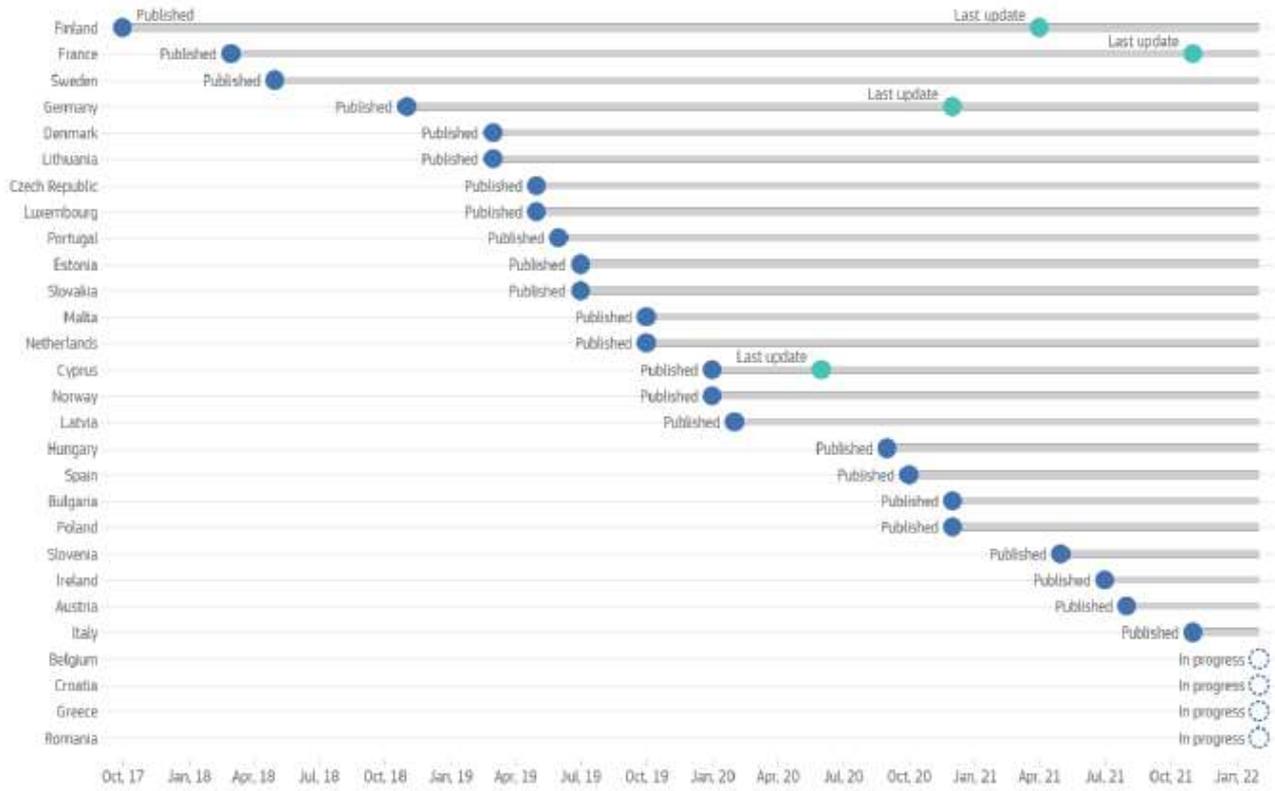
AI Watch European Landscape on the Use of Artificial Intelligence by the Public Sector



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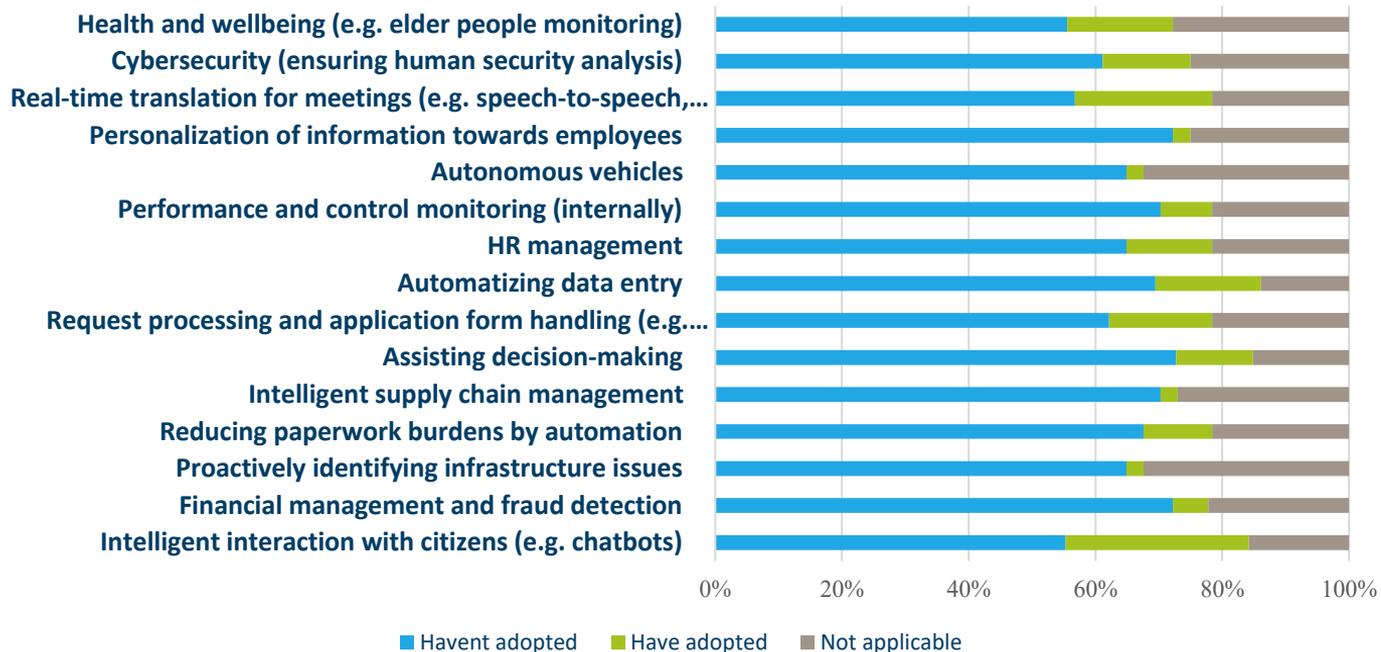
Artificial Intelligence goes public



AI has gained traction in public bodies.
However, we need to know:

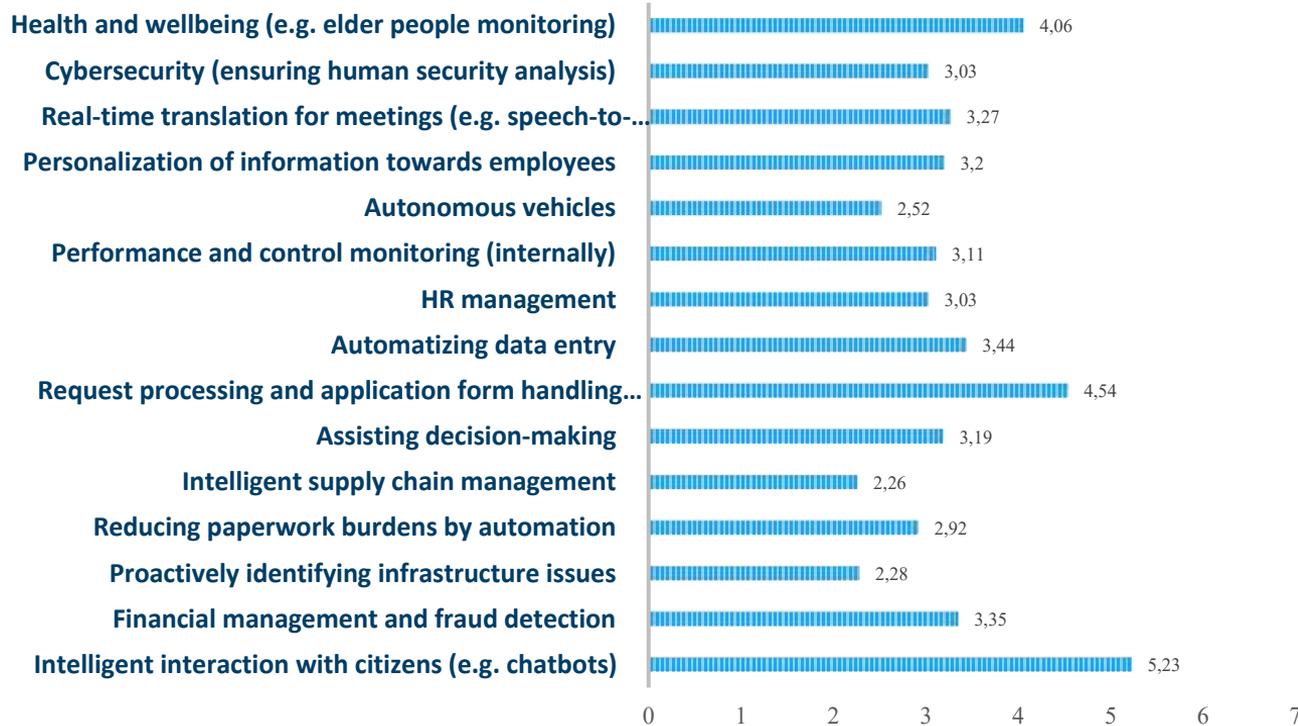
- Where do public bodies use AI?
- Where will they focus their efforts in the next years?
- What major challenges do they face?

Level of adoption by area of use



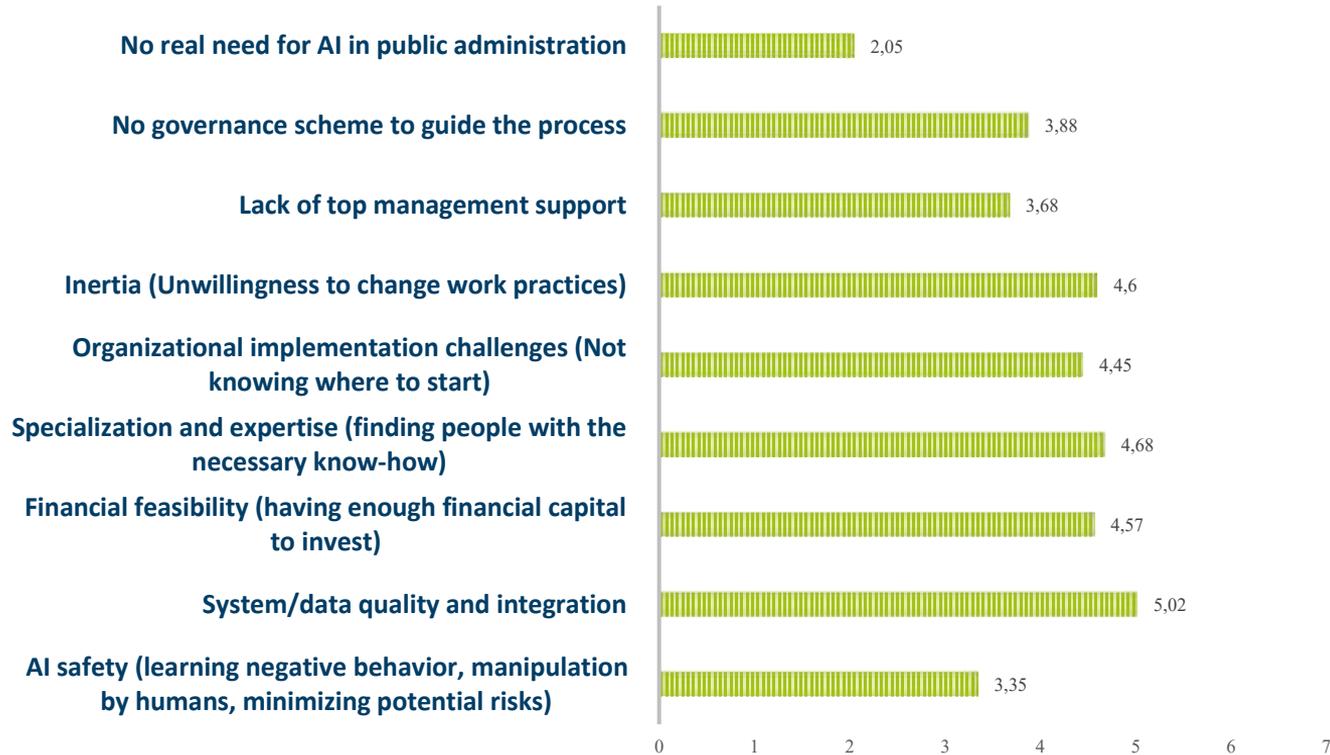
- Intelligent interaction with citizens most adopted (28.9%)
- Speech-to-speech and speech-to-text applications (21.1%)
- Request processing and application handling (15.7%)

Future intention to adopt AI



- Intelligent interaction with citizens ranks highest (5.23)
- Request processing and application form handling (4.54)
- Health and well-being applications of AI (4.06)

Challenges in adopting AI



- System/data quality ranks highest (5.02)
- Specialization and expertise is an important concern (4.68)
- Inertia – Organizational "Stickiness"(4.60)
- Financial feasibility (4.57)

European landscape on AI

1. Analysis of the AI national strategies with a focus on the public sector
2. Inventory of use cases of AI in the public sector
3. In-depth case studies





The importance of governance



Paul P. Tallon, Loyola University Maryland

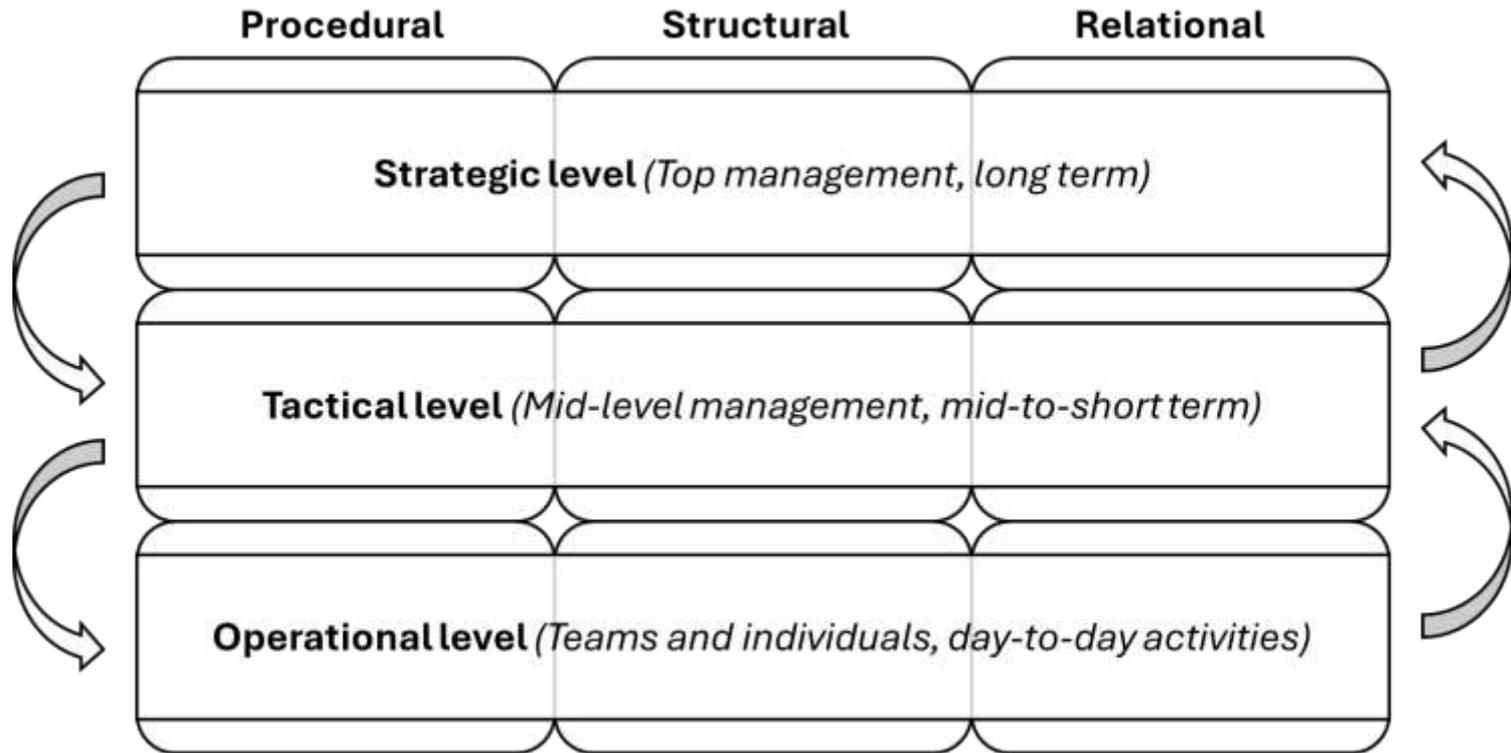
Corporate Governance of Big Data: Perspectives on Value, Risk, and Cost

Structural practices are responsible for determining key IT and non-IT decision makers and their corresponding roles and responsibilities when it comes to data ownership, value analysis, and cost management.

Operational practices are revolved around the processes and ways by which organizations execute information governance (e.g. data migration, data retention, cost allocation, data analytic procedures).

Relational practices are concerned with the formalized links between employees of the technical and business sides. They encapsulate practices and means of knowledge sharing, education and training, and strategic planning

Governance



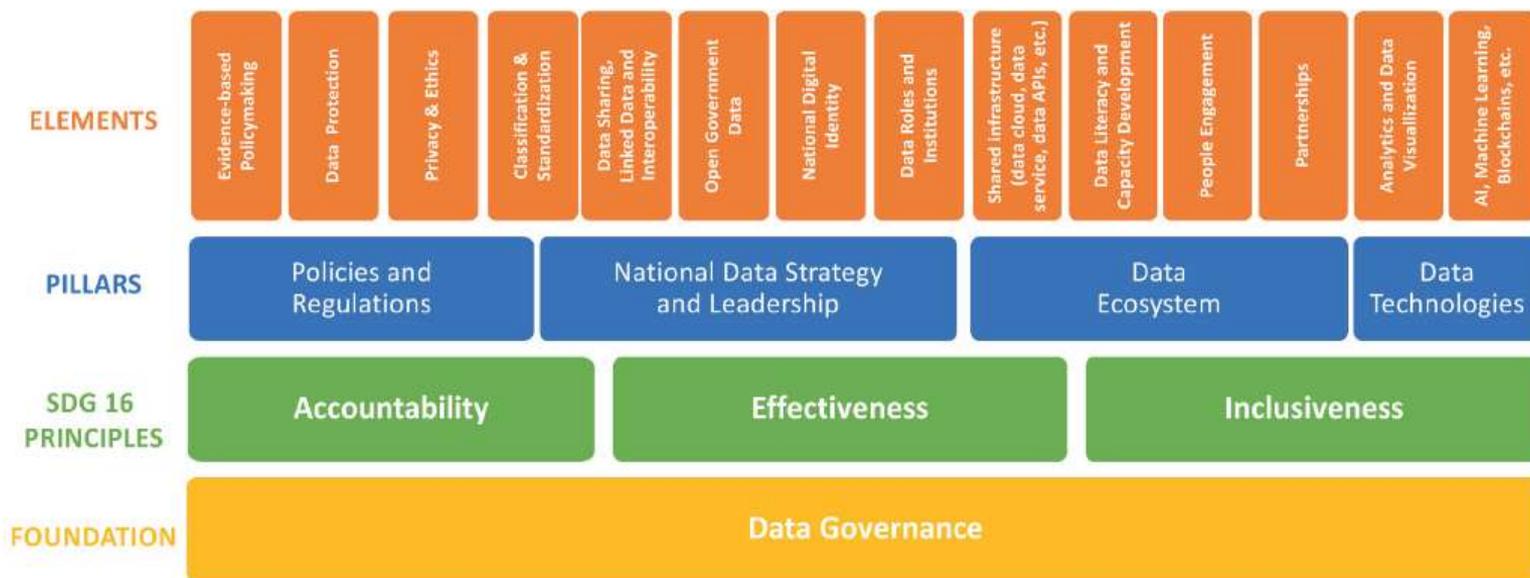
Governance practices for AI in the public sector

	Procedural	Structural	Relational
Strategic level	<ul style="list-style-type: none"> • Developing ethical AI guidelines • Compliance protocols • Establishing accountability procedures 	<ul style="list-style-type: none"> • Defining data stewards • Establishing independent ethics committees • Developing an ethical code of conduct • Establishing cybersecurity department 	<ul style="list-style-type: none"> • Establishing communities of practice • Stakeholder education and training • Experimentation and idea generation • Fostering knowledge transfer
Tactical level	<ul style="list-style-type: none"> • Minimizing authorization to access data • Developing explainability frameworks • Monitoring AI usage • Developing AI protocols for standardization • Ensuring security of algorithmic operation • AI lifecycle management processes 	<ul style="list-style-type: none"> • Safety barriers to prevent misuse • Establishing algorithmic registries • Defining project ownership • Developing steering group • Elimination of algorithmic censorship 	<ul style="list-style-type: none"> • Negotiating and contracting with vendors • Promoting society-in-the-loop activities
Operational level	<ul style="list-style-type: none"> • Data management • Establishing system/and data integration • Developing processes for elimination of bias • Establishing algorithmic transparency • Model reusability 	<ul style="list-style-type: none"> • Process-based interactions between people and AI • End-user participation in AI development and evaluation • Ensuring human monitoring and supervision of AI decision-making 	<ul style="list-style-type: none"> • Promoting collaborative efforts between stakeholders • Educating users to develop trust towards AI

Data governance for e-government



Figure 1
Illustrative data governance framework for e-government



Source: UN DESA (2020). UN E-Government Survey 2020, p. 166.

Data in use

The image shows the homepage of the DeepSea website. The background is a dark blue topographic map of the world's oceans. A glowing blue line represents an optimized shipping route, starting from the top left and ending at a large cargo ship in the bottom right. The ship is shown from a top-down perspective, with its deck and cargo containers visible. The text is white and cyan, providing a high-contrast look against the dark background.

deepsea

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Steffen Fagerberg, VP Marine Operations, Maersk Line

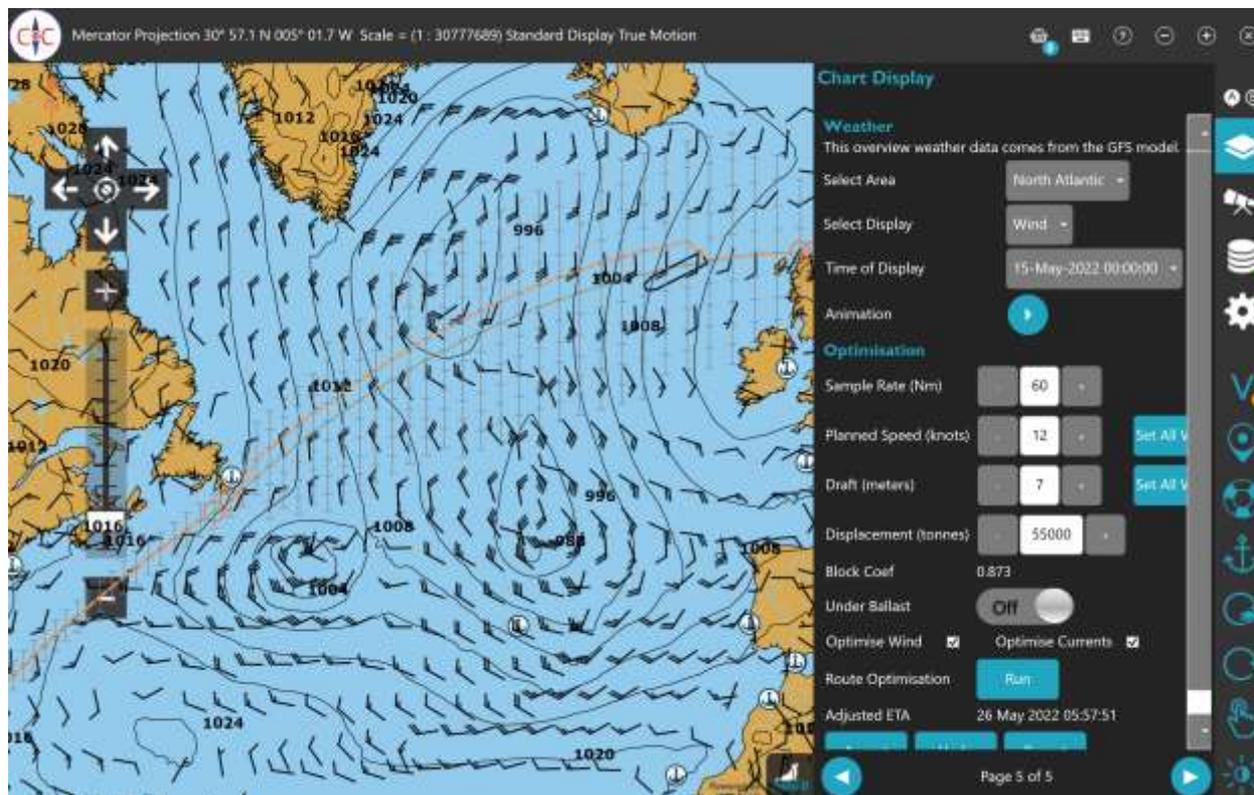
Data in use



Data in use



Data in use

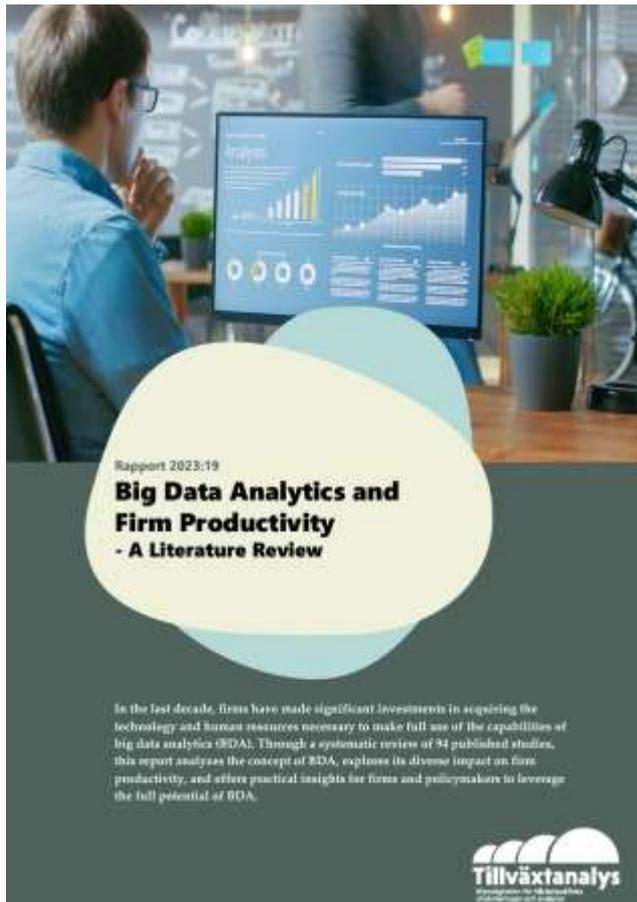


Data in use



The ambiguity of data



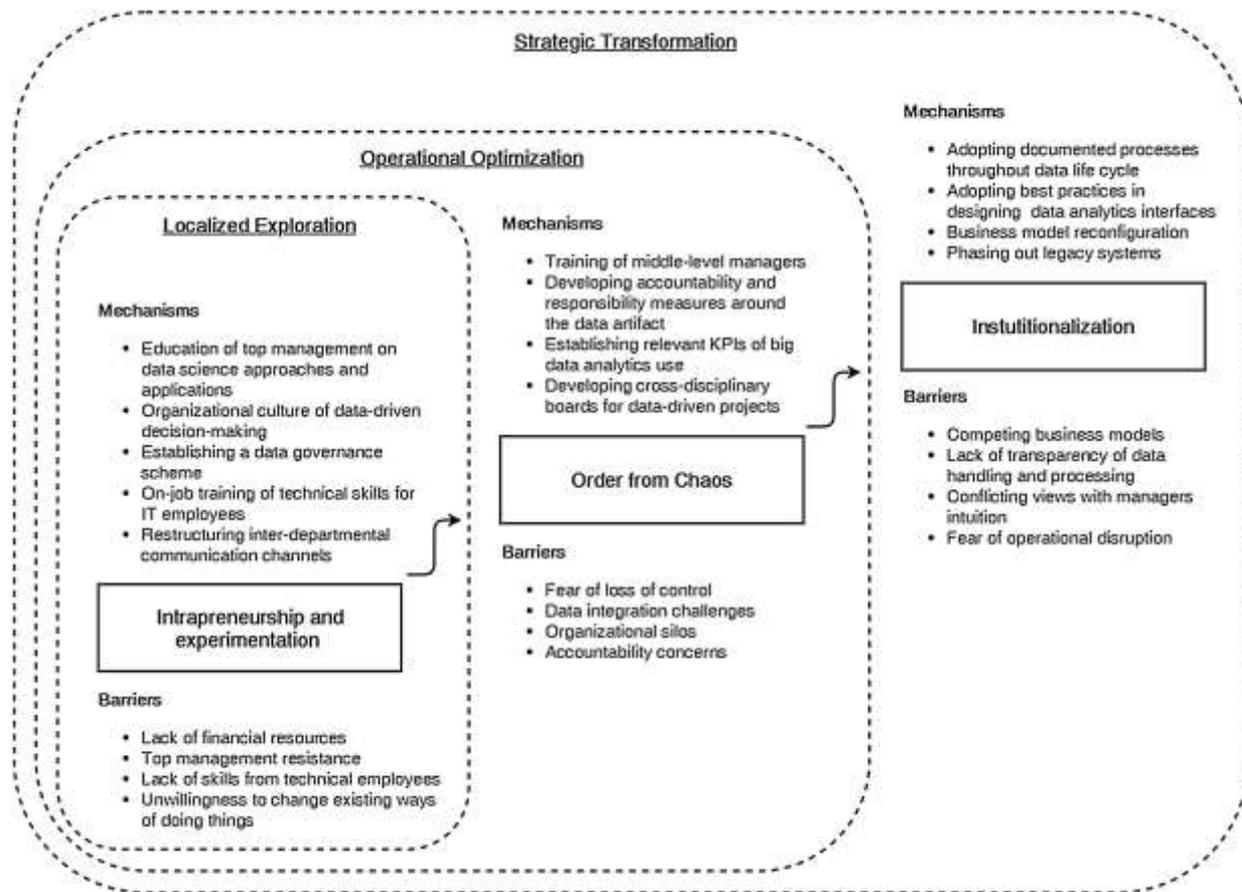


Lag effects in realizing productivity gains from BDA investments

Following the adoption of BDA projects, according to studies it typically takes at least one year, with an average of two years, before most firms begin to witness tangible improvements in terms of performance gains. This delay differs from the adoption of other technologies that these firms commonly embrace. The lag effects are attributed to the multifaceted requirements of BDA, which necessitate substantial preparatory work, experimentation, and testing before its applications can be effectively integrated into operations.

The effects of BDA are contingent upon industry and application uses

Studies suggest that the malleability of BDA depends on both internal and external factors. BDA applications can be applied to a wide range of industries, and their ability to create value depends on both the specific industry in which they are implemented and the processes they are intended to automate or enhance. For instance, certain industries that use physical devices to generate and collect data can more closely monitor and optimize processes. In addition, firms that operate in the same industry can have vastly different uses for their BDA investments, resulting in differentiating productivity gains.



Discussion and Questions

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