



Study Report

AI-enabled Decision-Making Support Tools (AI DMST) for Agriculture

Analysis of market dynamics, technical requirements, and stakeholder perspectives

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AI DMST

Seizing opportunities of AI-enabled decision-making support tools (AI DMST) in agriculture to support a diversified innovation ecosystem, sectoral performance, and competitiveness

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Executive Summary

A qualitative assessment of market dynamics, technical requirements, and policy options for AI-enabled Decision-Making Support Tools (AI DMST) in EU agriculture

AI-enabled Decision-Making Support Tools (AI DMST) offer substantial potential for advancing the sustainability, productivity, and competitiveness of European agriculture. Despite significant investment and innovation, the uptake of these tools remains fragmented due to structural, technical, economic, and regulatory barriers, especially affecting SMEs and individual farmers.

This study, commissioned by the European Commission's DG CNECT, assesses the market conditions, technical requirements, and stakeholder perspectives shaping the AI DMST landscape in Europe. Drawing on desk research, expert interviews, and stakeholder validation, the study identifies critical systemic gaps including limited access to high-quality data, fragmented infrastructure, lack of AI transparency, and unclear regulatory pathways.

To address these challenges, recommendations are structured into three clusters reflecting different intervention timespans: immediate actions, medium-term actions, and long-term structural measures.

Immediate actions (Cluster A) focus on reducing adoption barriers and accelerating innovation. These include promoting agricultural data interoperability, funding public data annotation and repository services, providing clear compliance guidance and regulatory sandboxes, supporting large-scale demonstration projects to showcase certified and explainable AI DMST solutions, and improving SME access to AI Factories through targeted voucher schemes.

Medium-term interventions (Cluster B) aim to strengthen economic incentives and build strategic digital capabilities. Key measures include integrating certified AI DMST into CAP eco-schemes to reward sustainable practices, expanding AI Factories and supporting the development of open, agriculture-specific foundation models, and establishing a dedicated EU observatory to monitor AI DMST market developments and infrastructure risks.

Long-term structural reforms (Cluster C) address foundational issues of market structure and digital sovereignty. Recommended actions include reviewing the effectiveness of current legislation (such as the Data Act) and mandating open API access in agricultural equipment if interoperability remains limited, as well as co-financing a rural edge-cloud backbone to support AI deployment and ensure inclusive access to advanced digital infrastructure across Europe.

More on the **background, objectives, and policy context** of this study can be found in Chapter 1.

Chapter 2 outlines the study's **scope and methodological approach**, including the types of stakeholder input.

An overview of the **current market landscape, key actors, and ecosystem dynamics** is presented in Chapter 3.

Technical requirements, data sources, and infrastructure needs for AI DMST are discussed in Chapter 4.

The results of the **stakeholder validation workshop and key hypothesis trends** are summarized in Chapter 5.

Chapter 6 provides **policy conclusions and actionable recommendations** to support a competitive and inclusive AI DMST market.

How to read the study

This study is organized as a progressive evidence-building narrative:

1. **Context - Chapter 1.** Introduces the policy background and explains why AI-enabled Decision-Making Support Tools (AI DMST) matter for Europe's digital and green objectives.
2. **Method - Chapter 2.** Sets out the scope, data sources, and qualitative methods used to generate reliable insights.
3. **Evidence - Chapters 3 & 4.** Provide the market analysis (actors, structures, data access) and the technical-infrastructure assessment that ground the study in real-world conditions.
4. **Findings - Chapter 5.** Synthesizes interview and workshop results into four validated systemic gaps that hinder AI DMST adoption.
5. **Recommendations - Chapter 6.** Translates those gaps into a sequenced policy agenda (immediate, medium-term, structural) and complementary actions for Member States and industry.
6. **Outlook - Chapter 6.4.** Concludes with future scenarios, open research questions, and a call for adaptive governance to keep policy aligned with innovation.

Reading straight through provides the full evidence chain; readers seeking only the policy take-aways can move directly from the introductory pages to Chapter **6**.

Contents

1	Introduction	6
1.1	Policy Context	6
1.2	Technical Foundations and Adoption Challenges	6
1.3	End-User Trust and Usability Issues	6
1.4	Purpose and Analytical Focus of this Study	7
1.5	Expected Contribution	7
2	Scope and Methodology.....	8
2.1	Scope	8
2.2	Methodological Approach	8
2.3	Analytical Methods	9
3	Market Dynamics and Ecosystem Landscape.....	10
3.1	Overview of the AI-enabled Decision-Making Support Tools (AI DMST) Market	10
3.2	Key Market Actors and Value Chain	21
3.3	Market Structures and Power Dynamics	25
3.4	Adoption Barriers and Market Failures	28
3.5	Innovation Drivers and Ecosystem Opportunities	30
4	Technical Requirements for AI DMST	35
4.1	Introduction and Scope	35
4.2	AI Development Lifecycle in Agricultural AI DMST	36
4.3	Scenario-Based Effort Profiles	36
4.4	Data Sources and Access Constraints	43
4.5	Deployment Infrastructures and Connectivity Challenges	44
4.6	System Integration and Explainability	46
4.7	Summary of Technical Needs and Gaps	46
5	Hypothesis Validation and Workshop Synthesis.....	48
5.1	Introduction	48
5.2	Cross-Cutting Reflections and Themes	48
5.3	Thematic Gap Analysis	50
5.4	Summary	55
6	Recommendations.....	56
6.1	Introduction	56
6.2	Key Systemic Gaps and Strategic Levers	57
6.3	Policy Recommendations	58
6.4	Outlook and Closing Remarks	64
7	Annex	67
7.1	List of Validated Hypotheses	67
7.2	Glossary	70
7.3	References	71

1 Introduction

Context, objectives, and policy relevance of the study

The European Commission, through its Directorate-General for Communications Networks, Content and Technology (DG CNECT), has launched this study to explore the market conditions, technical requirements, and policy implications of AI-enabled Decision-Making Support Tools (AI DMST) in the agricultural sector. The study is part of a broader effort to strengthen the European Union's digital and green transitions and to unlock the transformative potential of data and advanced technologies across economic sectors.

1.1 Policy Context

This initiative contributes to a strategic agenda that includes major policy and legislative efforts such as the Common European Agricultural Data Space (CEADS), the AI Act, the Data Act, the Data Governance Act, and various Horizon Europe projects. These initiatives aim to build a resilient digital single market for data, foster innovation, exploit the potential of AI, and contribute to sustainability goals. Within this evolving policy landscape, AI DMST are seen as critical enablers of precision agriculture and sustainable farming practices - integrating technologies such as Artificial Intelligence (AI), the Internet of Things (IoT), cloud and edge computing, and advanced data infrastructures.

1.2 Technical Foundations and Adoption Challenges

The effectiveness of AI DMST depends heavily on access to high-quality, timely data from a variety of sources - ranging from open-access weather data to sensor-based field data. IoT technologies play a key role in enabling real-time data collection and integration. At the same time, AI - including both classical and generative models - is becoming integral to many decision-support systems, placing additional demands on computing and connectivity infrastructure.

Despite significant investment, many promising digital tools struggle to reach or sustain market adoption. Structural barriers persist, including unequal access to valuable datasets. Larger firms (e.g. agro-chemical companies or machinery manufacturers) often control proprietary data and offer bundled services. In contrast, smaller actors are frequently constrained to public datasets of lower resolution or quality. High technical complexity, infrastructure needs, and financial thresholds reinforce these market asymmetries.

1.3 End-User Trust and Usability Issues

From the farmer's perspective, the current landscape often lacks impartial, affordable, and user-friendly tools. Persistent concerns include trust, transparency (particularly for AI-generated recommendations), and the administrative burden of adopting new digital systems. Farmers may also find it difficult to evaluate the suitability or quality of available AI DMST solutions, especially when confronted with opaque or non-interoperable systems.

1.4 Purpose and Analytical Focus of this Study

This study addresses the gap in understanding market conditions, technical requirements, and policy implications shaping AI DMST adoption in European agriculture. Specifically, it analyzes:

- The structure and dynamics of the AI DMST provider landscape
- Technical needs and maturity of different AI technologies (classical and generative AI)
- Data quality, availability, and governance frameworks
- Infrastructure requirements across the AI model lifecycle (development to deployment)
- Regulatory frameworks and their influence on innovation and adoption

Combining desk research, extensive expert interviews, and a stakeholder validation workshop, this study synthesizes insights from key stakeholders - including technology providers, researchers, policymakers, and industry actors - to identify critical adoption barriers, systemic gaps, and strategic levers for improvement

1.5 Expected Contribution

The findings from this study will directly inform strategic EU initiatives aimed at strengthening data ecosystems, enhancing AI innovation capacity, and addressing infrastructure bottlenecks in agriculture. The recommendations outlined will support policy development within the next Multiannual Financial Framework and contribute meaningfully to ongoing dialogues about digital transformation and agricultural innovation at the European and national levels.

2 Scope and Methodology

Analytical boundaries, stakeholder engagement, and validation approach

This study follows a structured, qualitative approach to assessing the market dynamics, technical requirements, and policy implications of AI-enabled Decision-Making Support Tools (AI DMST) in the EU agricultural sector. The methodology is designed to deliver in-depth insights while remaining proportionate to the study's scope and resources.

2.1 Scope

The study focuses geographically on the European Union, with selected references to international developments for context and benchmarking. Thematically, it examines the intersection of digital technologies - particularly Artificial Intelligence (including generative AI), Internet of Things (IoT), data platforms, and cloud/edge infrastructure - with agricultural innovation and policy.

As agreed in the study scope, direct engagement with farmers was limited; to ensure their perspectives are represented, we supplemented our interviews with insights from previous Fraunhofer IESE surveys and publicly available agricultural case studies.

The analysis emphasizes the supply side of the AI DMST ecosystem. It explores provider roles, technical and infrastructural requirements, data sources, and interactions within the broader digital ecosystem. While direct engagement with end users (i.e., farmers) was limited, their perspectives were reflected indirectly through referenced studies, workshop contributions, and the stakeholder backgrounds of participants.

2.2 Methodological Approach

The research was conducted in three phases:

Phase 1: Exploration

Initial desk research was carried out to review literature, policy documents, and relevant market analyses. This was complemented by 17 semi-structured expert interviews with stakeholders across the agricultural innovation ecosystem - including technology providers, agro-industrial actors, policymakers, researchers, and representatives of the farming community.

Interview sample:

- 17 participants from Germany, Denmark, Spain, Finland, Italy, the Netherlands, Romania, Sweden, and the USA
- 11 with international or EU-wide market experience
- Stakeholder types: technology providers, domain actors, machinery manufacturers, policymakers, startups, researchers, and farmers

While the sample showed a concentration in Germany, the high degree of EU-wide experience among stakeholders helped ensure that results reflect pan-European market dynamics. Moreover, stakeholder responses were consistent across national contexts, strengthening the reliability of the findings.

Phase 2: Analysis and Validation

Interview and desk research insights were analyzed using thematic qualitative methods to identify recurring challenges, patterns, and structural issues. A validation workshop with diverse experts was held to test preliminary findings, refine hypotheses, and surface additional gaps or opportunities. This step served to strengthen the robustness of the final conclusions and recommendations.

Phase 3: Synthesis and Reporting

The final phase integrated the various inputs into a coherent narrative aligned with the study's objectives. While a quantitative survey was initially considered, it was ultimately not conducted. A future survey may be useful to further validate key themes or gather broader feedback.

2.3 Analytical Methods

The study employed several qualitative methods:

- **Thematic analysis** was used to identify and categorize insights from interviews and workshop discussions across core themes such as data access, infrastructure, adoption, and governance.
- **Scenario thinking** supported the development of realistic AI DMST use-case profiles, illustrating variation in technical needs and deployment feasibility.
- **Comparative reflection** enabled contextualization of EU dynamics in relation to developments in other regions, especially on data governance and AI infrastructure.

These methods enabled a grounded, multi-perspective view of a rapidly evolving field, offering a basis for actionable recommendations and strategic guidance.

3 Market Dynamics and Ecosystem Landscape

Actors, structures, and barriers in the evolving AI-enabled Decision-making Support Tool (AI DMST) landscape

The following analysis of the market landscape for AI-enabled Decision-Making Support Tools (AI DMST) in EU agriculture is based on a combination of desk research and qualitative insights gathered through 17 expert interviews and a stakeholder workshop. Participants represented a diverse range of market actors, including technology providers, agribusinesses, research institutions, and regulatory bodies. The findings reflect the perspectives of those involved in the development and provision of AI- and IoT-enabled AI DMST, with a particular focus on structural trends, barriers to entry, and ecosystem dynamics. While the perspectives of end users (e.g., farmers) were not captured in high numbers, their perspective was indirectly supported through workshop inputs and referenced literature.

3.1 Overview of the AI-enabled Decision-Making Support Tools (AI DMST) Market

AI-enabled Decision-Making Support Tools (AI DMST) are widely regarded as a cornerstone of the digital transformation in agriculture. Designed to enhance the quality, speed, and sustainability of decisions made by farmers and agricultural businesses, these tools combine data, expert knowledge, and - more recently - artificial intelligence (AI) to offer context-sensitive guidance across a variety of use cases. AI DMST are increasingly expected to contribute to both policy ambitions and operational efficiency, supporting precision agriculture, resource optimization, and long-term strategic planning.

In practice, however, the AI DMST market in agriculture remains highly fragmented, difficult to quantify, and uneven in terms of maturity and adoption. While significant public and private investments have supported the development of AI-enabled solutions, many tools remain at the pilot or prototype stage. Market visibility is often limited, particularly for small and medium-sized providers. Several interviewees referred to a persistent “last mile” challenge: solutions that are technically sophisticated but fail to translate into real-world, scalable use due to usability, integration, or ROI-related hurdles. Likewise, farmers and advisors continue to face difficulties in evaluating the benefits, usability, and trustworthiness of available tools.

A recurring observation from stakeholder interviews and the workshop is that the provider side of the AI DMST ecosystem is underexplored in both research and policy. While some data is available on adoption patterns and farmer preferences, much less is known about the organizations that

develop, maintain, or distribute AI DMST. This knowledge gap complicates efforts to design supportive policy frameworks or targeted interventions, as it remains unclear which barriers are structural, which are technological, and which stem from regulatory uncertainty or market incentives.

3.1.1 Typology of AI DMST

To bring clarity to this landscape, the study applies a working typology of AI DMST that reflects current developments in AI applications for agriculture. This typology, summarized in Table 1, distinguishes six functional classes of AI DMST:

Table 1: Typology of AI DMST Use Cases Classes in Agriculture

AI DMST Class	Description & Example	Key AI Technologies	Key Impact Dimensions
Operational	Real-time field or stable actions <i>e.g., automated spraying, smart feeding</i>	Computer Vision, Edge AI, Reinforcement Learning	Efficiency, input reduction, labor savings
Tactical	Short- to mid-term planning <i>e.g., harvest scheduling, feed optimization</i>	Predictive ML Models, Time Series Forecasting	Cost control, planning accuracy
Strategic	Long-term scenario or investment planning <i>e.g., crop rotation strategies</i>	Simulation, Bayesian Networks, ML Ensembles	Sustainability, long-term ROI, risk reduction
Diagnostic	Issue detection and early warnings <i>e.g., disease or stress detection</i>	Anomaly Detection, Computer Vision, ML Classifiers	Productivity protection, early response
Advisory	Contextual guidance, often GenAI-based <i>e.g., chatbot for subsidy advice</i>	Generative AI (LLMs), NLP, Retrieval-Augmented Generation (RAG)	Accessibility, non-expert support
Integrated	All-in-one platforms <i>e.g., farm management with IoT and finance modules</i>	Hybrid Systems, Rule-Based + ML + IoT Integration	Coordination, usability, holistic oversight

Each class is associated with different AI technologies (e.g., computer vision, predictive modelling, natural language processing) and aims to address distinct impact dimensions - ranging from cost control and productivity protection to usability and holistic coordination. Interviewees frequently noted that specific technical and economic challenges - such as explainability, scalability, or ROI visibility - tend to cluster around particular AI DMST classes. For example, advisory and diagnostic tools often face credibility and trust barriers, while integrated platforms are reported to be complex and demanding in terms of data integration and user interface design.

This typology provides a conceptual anchor for the subsequent sections of this chapter. It is used to organize insights on market actors, value creation logics, barriers to adoption, and emerging opportunities. While the framework is not exhaustive, and the categories may overlap in practice,

it offers a practical lens through which to interpret stakeholder observations and potential policy implications.

3.1.2 Concrete Examples of AI DMST Classes

To illustrate the six AI DMST classes with real-world applications, we provide two representative examples per class. Each example highlights the use case, the core AI technology involved (including LLMs or generative AI where applicable), and the primary impact dimension.

Below, each AI DMST class is illustrated with two real-world examples. For each, we detail the use case, the core AI technology employed, and the primary impact dimensions addressed.

3.1.2.1 Operational (Real-time Field or Stable Actions)

Smart Droplets (smartdroplets.eu)

- Use case: Tractor- or drone-mounted micro-sprayers deliver ultra-low-volume droplets to individual weed targets identified via on-board imaging, enabling spot treatment at the plant level.
- AI technology: Edge-deployed computer-vision models combined with reinforcement-learning-driven actuation logic to detect, classify, and target weeds in real time.
- Impact dimensions: Efficiency (up to 50 % reduction in herbicide use), input optimization (precise droplet placement), labor savings (automated, high-resolution spraying).

Smart Livestock Feeding (OECD 2022)

- Use case: Continuous monitoring of animal behavior and physiology to adjust feeding regimens dynamically.
- AI technology: Edge AI processing of real-time sensor streams (weight, movement, rumination) to predict nutritional needs.
- Impact dimensions: Cost control (optimized feed use), animal health (improved growth rates).

3.1.2.2 Tactical (Short- to Mid-Term Planning)

Harvest Scheduling Optimization (World Bank 2021)

- Use case: Recommends optimal harvest windows by integrating soil-moisture data, weather forecasts, and crop maturity models.
- AI technology: Predictive machine-learning models and time-series forecasting.
- Impact dimensions: Planning accuracy (reduced spoilage), risk reduction (avoiding adverse weather).

AI-Driven Feed Formulation (JRC 2022)

- Use case: Generates weekly feed rations that balance nutritional requirements with feedstock availability.
- AI technology: Time-series forecasting and optimization algorithms.
- Impact dimensions: Sustainability (reduced waste), cost control (efficient feed use).

3.1.2.3 Strategic (Long-Term Scenario or Investment Planning)

Crop Rotation Simulations (EPRS 2023)

- Use case: Models multi-year crop rotation under different climate and management scenarios to guide land-use investment.
- AI technology: Bayesian network simulations combined with machine-learning ensembles.
- Impact dimensions: Long-term ROI (maximized productivity), sustainability (soil health).

Generative Scenario Planning (McKinsey & Company 2023)

- Use case: Produces synthetic financial and operational scenarios across policy, price, and climate variables.
- AI technology: Generative AI techniques to simulate plausible farm-level outcomes.
- Impact dimensions: Risk reduction (informed investment), strategic insight (scenario comparison).

3.1.2.4 Diagnostic (Issue Detection and Early Warnings)

LLaMA-Powered Plant Health Monitoring (Meta AI 2023)

- Use case: Analyses aerial or ground images to detect early disease symptoms before visible damage.
- AI technology: Transfer-learning-based computer-vision classifiers fine-tuned on plant imagery.
- Impact dimensions: Early response (reduces yield loss), productivity protection.

Multispectral Stress Detection (FAO & ITU 2020)

- Use case: Flags water stress and nutrient deficiencies via multispectral sensor data analysis.
- AI technology: Anomaly-detection algorithms processing multispectral indices.
- Impact dimensions: Resilience (prevents crop failure), yield protection.

3.1.2.5 Advisory (Contextual Guidance, Often GenAI-Based)

Alpaca LLM-Based Assistant (Stanford University 2023)

- Use case: Interactive chatbot offers tailored advice on subsidies, regulations, and best practices.
- AI technology: Fine-tuned large language model (LLM) for instruction following.
- Impact dimensions: Accessibility (non-expert support), decision confidence.

PlantVillage Nuru (FAO & ITU 2020)

- Use case: Mobile app diagnoses crop diseases from user-captured photos and suggests management measures.
- AI technology: On-device convolutional neural networks (CNNs) for image classification.
- Impact dimensions: Accessibility (expertise at scale), early response.

3.1.2.6 Integrated (All-in-One Platforms)

Agri-Platform Startups (AgFunder 2023)

- Use case: Unified dashboards combine IoT field data, AI analytics, and financial planning tools.
- AI technology: Hybrid systems integrating rule-based logic with ML pipelines and IoT integration.
- Impact dimensions: Coordination (end-to-end oversight), accessibility.

R4Agri Project (DFKI 2024)

- Use case: Modular platform delivers real-time monitoring, tactical planning, and strategic forecasting in one suite.
- AI technology: Rule-based engines, ML models, and IoT data fusion in a hybrid architecture.
- Impact dimensions: Holistic oversight, efficiency.

Summary

Each class features one established commercial solution and one emerging or research-driven tool to highlight both technological maturity and innovation potential. This structured overview demonstrates the diverse AI methodologies - from edge-based computer vision to LLMs and generative models - and underscores how different AI DMST classes address distinct impact dimensions, informing the need for tailored technical and policy support.

We chose two examples per class to showcase both breadth and maturity across AI DMST applications - from established commercial systems to pioneering research initiatives. Each case demonstrates a clear AI component (classical machine learning, computer vision, LLMs, or generative AI) and aligns with one of the core impact dimensions (efficiency, planning accuracy, sustainability, risk reduction, or accessibility). This diversity underscores the necessity for differentiated policy measures and technical support tailored to varying levels of technological readiness and use-case complexity.

3.1.3 Impact Dimensions for AI DMST

AI-enabled Decision-Making Support Tools (AI DMST) generate a wide spectrum of benefits in the agri-food sector. To streamline our analysis and policy discussion, we organize these benefits into five broad impact categories, each encompassing a set of key impact dimensions most relevant for AI DMST.

Operational Efficiency

AI DMST automate routine tasks and optimize resource use, driving immediate on-farm improvements.

- Efficiency & Resource Optimization: Reducing inputs (water, chemicals, feed) through precision interventions such as spot spraying or smart feeding.
- Coordination & Holistic Oversight: Unifying disparate data streams (IoT, financial, field observations) into single dashboards for seamless workflow management.

Economic Performance

By improving planning and forecasting, AI DMST enhance farm profitability and investment decisions.

- **Cost Control & Economic Benefit:** Lowering operational expenses via optimized resource allocation and clear ROI visibility.
- **Planning Accuracy & Decision Confidence:** Strengthening short-term (harvest, irrigation) and long-term (crop rotation, capital planning) schedules through predictive and scenario-based models.

Resilience & Risk Management

Early warning and scenario analysis help farms withstand shocks and uncertainty.

- **Risk Reduction & Resilience:** Detecting diseases or stress pre-emptively and simulating adverse weather or market conditions to guide proactive interventions.
- **Traceability & Accountability:** Enabling end-to-end tracking of inputs and outputs - critical for rapid recall, liability management, and certification schemes.

Sustainability & Quality Assurance

AI DMST support environmentally responsible practices and maintain food-safety standards.

- **Sustainability & Environmental Impact:** Promoting soil health, biodiversity, and efficient water/nutrient use through precision planning and monitoring.
- **Food Safety & Quality Assurance:** Monitoring contamination risks, optimizing harvest timing, and flagging post-harvest storage issues to meet regulatory and consumer requirements.

Governance & Accessibility

Embedding compliance mechanisms and democratizing expertise lowers barriers and ensures trust.

- **Regulatory Compliance & Governance Support:** Automating audit logs, report generation (e.g., for CAP or AI Act), and in-tool compliance checks reduces manual overhead.
- **Accessibility & Democratization of Expertise:** Delivering expert guidance via LLM-powered chatbots or mobile apps - offered by both established providers and agile startups - making advanced recommendations available to non-specialist users.

The impact dimensions described above capture the range of benefits and transformative potentials that AI-enabled Decision-Making Support Tools (AI DMST) can provide across various agricultural activities. These include improved operational efficiency, enhanced sustainability outcomes, and better risk management, among others. Understanding these dimensions lays the foundation for assessing how AI DMST contribute to advancing European agriculture.

Note: This section does not cover adoption rates, investment costs, or operational resource requirements associated with AI DMST. These important market and usability factors are discussed in detail in Section 3.4 (Adoption Barriers and Market Failures). There, we explore how adoption varies by farm size, the economic challenges for smaller farms, and the human resource capacities necessary to effectively use these tools.

3.1.4 Complexity and Heterogeneity of Agriculture

Agriculture presents a uniquely complex and dynamic environment for AI-enabled Decision-Making Support Tools (AI DMST). Unlike controlled settings such as manufacturing halls or indoor farming facilities, outdoor farming operates within a continually changing biosphere influenced by environmental, climatic, and biogeographical factors. These conditions vary not only across regions but also over time, creating highly variable and often complex environments that challenge the development of scalable and robust AI solutions.

Within this broad context, agriculture includes diverse sectors such as crop production, horticulture, and livestock farming, each with specific operational needs and challenges. This sectoral variety, combined with the environmental variability, means that AI systems must be highly flexible and capable of handling complex, multi-dimensional data across different spatial and temporal scales.

In practical terms, these complexities imply that AI DMST developers face significant challenges in creating solutions that work reliably across diverse farming conditions. Models need to adapt to changing environments and be tailored to different agricultural practices, which makes generalization and scalability more difficult than in more controlled industries. Designing AI tools with this in mind is essential for truly effective decision support in agriculture.

3.1.5 Regulatory and Policy Environment

The regulatory and policy environment plays a critical role in shaping the development and adoption of AI-enabled Decision-Making Support Tools (AI DMST) in European agriculture. A comprehensive policy framework exists that directly influences how data is shared, how AI models are developed and deployed, and how digital infrastructures are built to support these innovations. This section outlines the most relevant EU-level instruments that impact the AI DMST ecosystem as discussed throughout this report.

The **AI Act** stands at the center of the EU's efforts to ensure the safe and trustworthy use of artificial intelligence. It introduces a risk-based regulatory framework, requiring that high-risk AI systems - some of which may include agricultural decision-support tools, e.g., automated systems - comply with strict requirements for transparency, accountability, and human oversight. For AI DMST developers and users, this means that AI tools used in these areas must meet clear standards, shaping their conceptual and technical design, the accompanying documentation, and the conformity-assessment process - thereby influencing their overall development cycle and market readiness.

Complementing this is the **Data Act**. The Act sets out certain provisions related to the right of users and third-party developers to access machine-generated data from connected devices - such as tractors, drones, and field sensors - on fair, reasonable, and non-discriminatory terms. By obliging data holders - e.g. equipment manufacturers and platform operators that control these data streams - to share the data upon request (subject only to cost-recovery fees), it holds the potential to break existing "data lock-in" and fosters interoperability, creating a more open data pool for AI DMST developers to train models and build innovative, data-driven tools.

The **Data Governance Act (DGA)** is designed to facilitate secure and trustworthy data sharing across sectors and Member States by introducing harmonized mechanisms for the re-use of certain data, the role of neutral data intermediaries, and voluntary data altruism. While the Data Act establishes rights to access certain machine-generated data, the DGA complements this framework by enabling organizations and individuals to make their data available for wider use under clear, trustworthy conditions. In practice, the DGA sets out the conditions under which data holders - including both public-sector bodies and private organizations - can share data securely, either via certified data intermediaries or through structures supporting data altruism. This cross-sectoral

approach is intended to foster the availability of high-quality data for innovative services, such as AI DMST in agriculture, by building confidence in data sharing, supporting interoperability, and ensuring compliance with EU rules and values.

In addition, the **Common Agricultural Policy (CAP)** remains a critical driver for digital innovation in the farming sector. Through eco-schemes and sustainability programs, CAP creates direct incentives for farmers to adopt technologies that support climate resilience and environmental sustainability. AI DMST can play a significant role in helping farmers meet these goals by optimizing input use and improving productivity. Recognizing and integrating certified AI DMST solutions into CAP incentive structures could therefore accelerate their adoption and contribute to achieving broader EU sustainability objectives.

Intellectual-property and liability context. Beyond data-access and governance rules, several horizontal IP and liability frameworks also condition how agricultural data and AI models may be reused. EU copyright and database legislation set the boundaries for text-and-data-mining exemptions, while trade-secrets rules govern the disclosure of proprietary models and training corpora. Forthcoming AI-specific product- and damage-liability instruments will further clarify risk allocation when AI-generated recommendations cause economic loss or regulatory non-compliance. These legal frameworks interact with the AI Act, the Data Act, and the Data Governance Act. Their combined impact determines whether the reuse of multimodal datasets (such as imagery, sensor streams, or agronomic text) and the fine-tuning of foundation models can be carried out in a legally secure manner by AI DMST developers and end users. Ongoing monitoring is needed to ensure legal certainty as these regulations evolve.

Europe's flagship research and deployment instruments - Horizon Europe, which supports collaborative research and innovation projects, and the Digital Europe Programme (DEP), which invests in large-scale digital capacities - together underpin the **EU's AI strategy**. Building on these, the **AI Factories** (see section 4.1.1) initiative provides shared AI infrastructure, regulatory sandboxes, and data services to lower barriers for SMEs and innovators. For the agricultural sector, the dedicated Agri-Food AI Factory supplies computing resources, domain-specific datasets, and testing environments to support the development, validation, and deployment of trustworthy AI DMST solutions. This blended funding model directly addresses several of the structural barriers identified in this study, such as limited access to affordable compute resources for smaller providers and the current reliance on cloud services from non-EU providers, ensuring that even smaller providers and nascent ventures can access affordable AI development resources and participate in the emerging European AI ecosystem.

Together, these policy instruments form a coherent framework that both governs and enables the digital transformation of European agriculture. Their effective implementation will be central to overcoming the systemic gaps identified in this report and ensuring that AI-enabled decision-support tools contribute meaningfully to a sustainable, competitive, and resilient agricultural sector.

Market Overview – Quick-Glance Summary

The EU market for AI-enabled decision-making support tools (AI DMST) is vibrant but fragmented.

EU fosters regulated, SME-led innovation but remains fragmented; China scales rapidly through state-led pilots; U.S. drives profit-focused adoption with low regulation.

Six functional classes dominate: operational, tactical, strategic, diagnostic, advisory, and integrated platforms.

Market visibility is low: many solutions remain at pilot stage and few achieve large-scale deployment.

Data asymmetries favor large equipment or input providers that control proprietary sensor streams.

Smaller innovators face three recurring hurdles: scarce high-quality datasets, costly compliance, and uncertain return-on-investment.

Adoption is slowest where tools are perceived as opaque (“black-box AI”) or difficult to fit into existing farm workflows.

Structural issues in data sharing, interoperability, and trust establish the context for the systemic gaps analyzed in Chapters 4 and 5.

3.1.6 Global Perspective on AI DMST Ecosystems

This section compares the AI-enabled Decision-Making Support Tool (AI DMST) landscapes in the European Union, China, and the United States, chosen for their leading roles in agricultural innovation, distinct regulatory frameworks, and significant market sizes that shape global AI development and adoption trends.

European Union: The EU fosters a dynamic, SME-led AI DMST market shaped by horizontal legislation such as the AI Act (European Commission, 2021) and Data Act (European Commission, 2022), alongside strong data privacy rules under the GDPR. The development of AI DMST is primarily driven by start-ups, research consortia, and public-private partnerships, supported by – among others - significant public funding through Horizon Europe and the Digital Europe Programme (European Commission, 2023).

Business models in AI DMST increasingly prioritize interoperability, data sovereignty, and environmental compliance as direct responses to evolving regulatory demands. The complex and stringent regulatory environment compels vendors to incorporate advanced transparency, risk-management, and sustainability features early in the development cycle. This, in turn, raises development costs and prolongs time-to-market, especially impacting smaller providers (DSSC, 2023).

Moreover, while these regulations aim to harmonize the market, their implementation varies across member states, and practical adoption of common data spaces like CEADS remains uneven (DSSC, 2023). This leads to market fragmentation across countries and value-chain segments, as solutions must often be customized to meet differing national interpretations of EU regulations and local data-sharing practices.

China: China follows a state-led model in which ministries and provincial governments fund and coordinate large-scale precision farming pilots (State Council Information Office, 2024). These

programs integrate real-time crop monitoring, computer-vision-guided pest control, autonomous machinery, and blockchain traceability under unified digital-agriculture strategies. The regulatory landscape is evolving rapidly, with increasing emphasis on data security, ethical AI use, and alignment with national strategic goals (Kovács, 2023). Notably, since 2022, China has been actively developing a national data space initiative aimed at enhancing cross-sector data sharing, interoperability, and governance - including in agriculture - to accelerate AI development and digital transformation.

Centralized governance enables rapid deployment through standardized data infrastructures and streamlined policy frameworks, reducing technical and administrative barriers (World Economic Forum, 2025). However, this deployment largely occurs in government-defined pilot zones rather than through competitive, open-market dynamics, limiting diversity in solutions and entrepreneurial innovation.

United States: The U.S. adopts a market-driven approach focused on profitability and rapid innovation cycles. Major equipment manufacturers and venture-backed start-ups dominate the market, offering proprietary, vertically integrated platforms increasingly enhanced by LLM-based advisory add-ons (Grand View Research, 2024).

Federal support is provided mainly through competitive research grants, such as those from USDA-NIFA and the NSF AI Research Institutes (USDA NIFA, 2024; NSF, 2024). However, overarching AI regulation specific to agriculture remains minimal (Farmonaut, 2025), with broader AI policy frameworks still under development at the federal level. Notably, the United States currently lacks dedicated sector-specific AI regulations for agriculture; instead, AI deployment in this sector is governed primarily by horizontal AI policies and existing agricultural, environmental, and data privacy regulations that are not AI-specific. The current regulatory environment is evolving rapidly and marked by significant uncertainty, as ongoing legislative efforts seek to balance innovation with transparency, ethics, and accountability. This dynamic creates a volatile landscape where the future shape of AI governance in agriculture remains unclear. This regulatory context enables faster product launches driven by near-term return on investment but often at the expense of standardized transparency, sustainability, trust mechanisms, and planning security.

Table 2: Comparative Overview of Global AI DMST Development Models

Factor	European Union	China	United States
Governance Model	Private innovation under strong regulatory oversight (EC, 2021)	Centralized, state-led coordination (SCIO, 2024)	Market-driven, minimal regulation (Farmonaut, 2025)
Investment Landscape	High public funding (incl. Horizon, Digital Europe); limited VC restricts scaling (EC, 2023)	Large-scale public investment with state-owned enterprises; CAGR 7.84% through 2029 (TechSci Research, 2023)	Mature VC ecosystem and competitive federal grants (USDA NIFA, NSF , 2024)
Data Governance	Strict interoperability and privacy via Data Act and GDPR ; fragmented data space adoption, with public agricultural datasets becoming increasingly accessible through initiatives like the developing Common European Agricultural Data Space (CEADS) and Copernicus (DSSC, 2023; European Commission, 2023; European Space Agency, 2024)	Centralized data pooling and standardized access through government platforms, including public sector and meteorological datasets (SCIO, 2024; CAICT, 2023; CMA, 2024).	Public datasets accessible but often tied to proprietary platforms (USDA , 2024)
Compute & Connectivity	AI Factories initiative, but high costs and rural broadband gaps limit real-time deployments (EC, 2023)	State investments ensure full coverage for pilot zones (WEF, 2025)	Hyperscaler clouds and private networks support broad services (Grand View Research , 2024)
Regulatory Impact	Strict requirements under AI Act delay market entry (EC, 2021)	Sector-specific guidelines streamline state-backed pilots (SCIO, 2024)	Minimal regulation enables fast deployment, lower trust safeguards (Farmonaut, 2025)

The **EU model** encourages responsible, sustainable AI DMST development but faces structural challenges. While the AI Act (European Commission, 2021) sets out rigorous compliance requirements, reports indicate that regulatory compliance increases development complexity and delays, particularly for SMEs (DSSC, 2023). The uneven implementation of data-sharing frameworks leads to fragmentation, as solutions must be adapted to differing national legal interpretations and data governance ecosystems.

China’s model achieves rapid deployment through centralized funding and policy direction, effectively overcoming data and infrastructure barriers (SCIO, 2024; WEF, 2025). However, it limits open-market competition, potentially constraining long-term innovation diversity.

The **U.S. model** emphasizes speed and profitability, supported by a mature VC ecosystem and low regulatory barriers. While this fosters rapid technological adoption (USDA NIFA, 2024; NSF, 2024), it often lacks unified safeguards for transparency and sustainability, resulting in fragmented trust standards across solutions (Farmonaut, 2025).

3.2 Key Market Actors and Value Chain

In the context of this study, it is important to distinguish between two interconnected value chains. The first is the agri-food value chain, which spans the full spectrum from agricultural input suppliers and primary production through processing, logistics, retail, and ultimately to consumers. The second is the value chain for AI-based solutions and services, which includes data providers, technology developers, system integrators, and support services that supply digital innovations to the agri-food sector.

This section focuses on the value chain for AI-based solutions and services, mapping the roles of key market actors and highlighting how they interact with and support the broader agri-food value chain. Understanding these relationships is crucial for assessing market dynamics, identifying innovation pathways, and evaluating the adoption of AI DMST in European agriculture.

3.2.1 Value Chain Perspective on AI DMST

AI DMST touch every stage of the agri-food value chain - from upstream breeding inputs to downstream consumer-facing certification. Rather than functioning as stand-alone apps, these tools are embedded in an ecosystem of actors who exchange data, domain know-how, and commercial value. Understanding “who hands what to whom” is essential for interpreting the market trends and structural barriers analyzed later in this chapter.

Table 3 summarizes what each stakeholder group contributes to the chain and where they experience AI DMST-specific frictions.

Table 3: Stakeholder roles in the value chain

Stakeholder type	Typical assets / inputs contributed	AI DMST-specific needs & pain points
Technology providers (software vendors, AI start-ups, device OEMs)	<ul style="list-style-type: none"> ▪ Algorithms, edge devices, SaaS platforms ▪ System integration expertise 	<ul style="list-style-type: none"> ▪ Access to clean, labelled domain data ▪ Interoperability standards for machine data ▪ Clarity on IP for co-developed models
Data-infrastructure & platform operators (cloud, connectivity, ag-data hubs)	<ul style="list-style-type: none"> ▪ Storage, compute, APIs, connectivity (5G, LoRa) 	<ul style="list-style-type: none"> ▪ Sustainable data-monetization model ▪ Agreed-upon semantics and ontologies ▪ Assurance on data-sovereignty rules
Domain actors (input firms, cooperatives, food processors, traders)	<ul style="list-style-type: none"> ▪ Domain knowledge, proprietary field/lab data ▪ Existing farmer networks 	<ul style="list-style-type: none"> ▪ Proof of ROI to justify data-sharing ▪ Liability allocation when AI advice fails
Researchers & innovators (universities, RTOs, accelerators)	<ul style="list-style-type: none"> ▪ Novel algorithms, benchmark datasets ▪ Experimental testbeds, peer review 	<ul style="list-style-type: none"> ▪ Long-term access to operational data ▪ Clear route-to-market for prototypes
Policymakers & regulators at EU and national levels	<ul style="list-style-type: none"> ▪ Incentive frameworks for end users (e.g., CAP eco-schemes) ▪ Public R&I funding programs ▪ Legislative and regulatory mandates (e.g., data sharing, compliance requirements) 	<ul style="list-style-type: none"> ▪ Ability to trace and audit AI-generated outputs/evidence ▪ Clear, harmonized metrics and KPIs for policy impact assessment ▪ Effective mechanisms for regulatory compliance monitoring supported by AI systems
Standardization bodies (public and private)	<ul style="list-style-type: none"> ▪ Development and publication of technical, data, and process standards ▪ Guidelines for interoperability, data formats, and ethical AI deployment ▪ Platforms for stakeholder engagement and consensus building 	<ul style="list-style-type: none"> ▪ Adoption and enforcement of standards across diverse actors ▪ Keeping standards up to date with rapid AI technology evolution ▪ Addressing gaps in AI-specific standards for agriculture
End users (farmers, advisors, supply-chain managers)	<ul style="list-style-type: none"> ▪ Operational data, tacit know-how, decision authority 	<ul style="list-style-type: none"> ▪ User-friendly interfaces ▪ Trust in model transparency & data privacy ▪ Fair value capture from shared data

Illustrative flow: variable-rate nitrogen advice

Exemplary use case: a cloud-based AI DMST advises wheat farmers on nitrogen fertilization.

1. **Data capture** – Multispectral drone imagery (Domain Actors) plus soil-lab results feed a trained CNN model (Technology Provider) hosted on an ag-cloud platform (Data-Infrastructure Operator).
2. **Processing & advice** – The model generates a variable-rate prescription map that the farmer uploads to a GPS-enabled spreader (End User).
3. **Immediate impact** – Field trials report $\approx 20\%$ fertilizer savings and $+3\%$ yield.
4. **Downstream benefit** – Processor receives grain with lower protein variance, reducing blending costs; Regulator gains auditable data stream to verify eco-scheme compliance.

This micro-example illustrates how **data and monetary value flow in opposite directions**: data move upstream from farm to model provider, while economic value (yield benefit, compliance premiums) flows downstream towards the farmer and the processor.

3.2.2 Key Stakeholders in the AI DMST Ecosystem

3.2.2.1 Technology Providers

This group includes developers of AI and IoT solutions, operators of agricultural platforms, and providers of enabling infrastructure such as cloud services. These actors are central to the technical evolution of AI DMST and are responsible for implementing algorithmic models, ensuring connectivity, and managing data pipelines.

Interview feedback points to significant challenges faced by technology providers, including limited access to clean, annotated agricultural data, difficulties in scaling pilots into mature products, and the need for explainability in AI models to gain trust from users. Several respondents emphasized the importance of modularity and interoperability to allow integration into existing farm systems. The need for lightweight, edge-compatible AI solutions was also mentioned, particularly in response to connectivity constraints in rural areas.

Despite being key enablers, technology providers often depend on partnerships with domain actors or integrators to access operational data and ensure market reach. While this was mentioned by a few interviewees, further empirical data would be needed to assess how widespread and structurally relevant this dependency is.

3.2.2.2 Domain Actors

Agro-Chemical Companies

These actors are among the largest data holders in the sector and play a significant role in shaping data availability and precision agriculture standards. Globally, only a small number of major agro-chemical providers dominate the market, concentrating data and technological influence among a few key players (ETC Group, 2022; OECD-FAO, 2023). Their position in the value chain allows them to embed AI DMST into existing advisory services or digital platforms. Interviews conducted for this study indicate that, despite strong innovation capacity, these companies often maintain limited openness and data sharing, resulting in siloed solutions.

Machinery Manufacturers

As providers of connected equipment, sensor networks, and onboard computing, machinery manufacturers serve as a key interface between the physical environment and digital systems. Their control over machine-generated data places them in a powerful position within the ecosystem. While they have pioneered several operational AI DMST use cases (e.g. variable-rate application or autonomous systems), integration with third-party systems was reported to be difficult in practice due to proprietary standards and missing interoperability.

Agribusiness Corporations

These actors operate across the supply chain and are increasingly interested in using AI DMST to optimize logistics, quality control, and traceability. Their capacity to offer bundled digital services, including AI DMST, positions them as both adopters and providers. Some interviewees described their role as a bridge between technology providers and end users, while others raised concerns about data access and standardization - especially the risk that dominant platforms might restrict interoperability or create vendor lock-in.

3.2.2.3 Policymakers and Regulators

Policymakers at EU and national levels play a shaping role by defining the legal, ethical, and funding frameworks under which AI DMST are developed and deployed. Relevant instruments include the AI Act, the Data Act, and initiatives to promote common European data spaces. Policymakers also determine the allocation of public funds across research and innovation (R&I), deployment of digital technologies, data infrastructure, and agricultural policy instruments such as the Common Agricultural Policy (CAP), thereby directly influencing both the pace and direction of digital transformation in the sector.

Stakeholders acknowledged the potential of these frameworks to support innovation and trust but also pointed to uncertainties and gaps. In particular, developers and SMEs noted difficulties in interpreting legal requirements and the lack of test environments for regulatory learning. Interviewees also highlighted the importance of stable, long-term infrastructure investments to support market access and interoperability.

3.2.2.4 Researchers and Innovators

This group comprises research institutions, universities, SMEs, and startups. Many of the most innovative AI DMST concepts originate in this segment, which benefits from proximity to scientific advances and agility in experimentation.

However, these actors face significant structural challenges. Multiple respondents cited the difficulty of accessing reliable training data, limited computing capacity, and the short-term nature of innovation funding. Several hypotheses validated during the workshop point to the need for shared infrastructure, open-source pipelines, and regulatory sandboxes to enable iterative and inclusive development.

Moreover, some feedback suggests that publicly funded research projects do not always prioritize usability, economic viability, or post-project market readiness. A stronger emphasis on real-world adoption, particularly in the late stages of R&I projects, could improve the transferability of innovations to operational settings.

Despite these constraints, researchers and innovators are seen as key contributors to the diversification of the AI DMST landscape.

3.2.2.5 End Users

Although not represented in large numbers in the interviews (two direct interviewees), end users - primarily farmers and farm advisors - are critical to the success of AI DMST. Their perspectives were additionally and indirectly considered through literature (e.g., national Bitkom surveys indicating that nearly half of farms explore or deploy AI tools), stakeholder workshop discussions, synthesis of prior studies, and internal deliberations with domain experts involved in related IESE initiatives and projects, e.g., Cognitive Agriculture (COGNAC) pilot evaluations, X-Kit AI toolkit prototyping sessions, BMEL "Agrardatenplattform" feasibility consultations, and FMIS user focus groups.

Several barriers to uptake were noted, including uncertainty about return on investment, lack of transparency in AI-generated outputs, and the complexity of integrated systems. Trust and usability were recurrent themes, particularly with regard to tools that offer prescriptive or advisory functionalities. The typology presented in section 3.1 helps to contextualize these concerns by clarifying the different types of support AI DMST can offer, and the varying levels of data, expertise, and interpretation required.

Numerous studies echo these findings, identifying high initial investment costs, economic uncertainty, limited digital skills, and concerns about data privacy and trust as core challenges to the adoption of digital and AI tools in European agriculture (Bitkom, 2024; Dibbern et al., 2024; European Parliamentary Research Service, 2023). Addressing these barriers will be essential to ensure broad and effective adoption of AI-enabled decision support tools among end users.

3.2.2.6 Summary

This overview of stakeholder roles lays the foundation for the following section, which explores the structural characteristics of the AI DMST market and the distribution of power, data, and infrastructure within it.

Together, these stakeholder groups form a complex and interdependent ecosystem around the development and deployment of AI DMST in European agriculture. While each plays a distinct role, their interactions and the conditions under which they operate often shape the pace, direction, and inclusiveness of innovation.

A more integrated value chain view is needed to understand where value is generated, captured, or lost. At present, bottlenecks often occur at the interfaces between actors - such as between data-generating equipment and AI developers, or between public research and commercial deployment. Understanding these structural gaps and friction points is critical for designing targeted support measures and policies that promote inclusive innovation.

3.3 Market Structures and Power Dynamics

3.3.1 Structural Characteristics of the AI DMST Market

The market for AI DMST in agriculture is still in a formative stage. Across interviews and the stakeholder workshop, participants consistently described the market as fragmented, unevenly developed, and marked by a lack of transparency about who provides what, to whom, and at what stage of maturity. Many tools exist in pilot or early deployment phases, and the absence of consolidated data on providers or usage makes it difficult to assess the scope and scale of the market with confidence.

It is important to note that the structure and maturity of the AI DMST market vary significantly across agricultural domains, use cases, and tool types. Some of the patterns and concerns raised in this section - such as access barriers, data asymmetries, or low tool comparability-may apply

more strongly to specific sectors (e.g. animal production, arable farming) or classes of AI DMST (e.g. advisory or integrated systems). This diversity must be considered when interpreting general trends and policy implications.

Stakeholders pointed to the limited availability of standardized and interoperable solutions across the market. While this issue affects all farm sizes, it disproportionately impacts small- and medium-sized farms, as most AI DMST remain tailored to specific farming contexts, equipment configurations, or value chains, rendering them ill-suited to the distinct needs and constraints of these smaller operations. As a result, tools are often not modular, making integration into existing farm operations more difficult. In addition, providers frequently depend on non-transparent or siloed data sources, limiting tool comparability and broader market development.

3.3.2 Provider Motivations and Business Model Trends

In addition to understanding adoption drivers among agrifood practitioners, it is essential to examine the motivations and business models of AI DMST providers. These factors directly influence the availability, scalability, and long-term viability of solutions in the market.

Several key factors currently drive providers to develop and market AI DMST solutions:

Recurring Revenue Models: Clear unit economics and predictable cash flows are primary considerations for providers when designing sustainable business models. A majority of leading suppliers offer Software-as-a-Service (SaaS) subscriptions combined with analytics-as-a-service packages, typically structured with tiered pricing based on data volume, functionality, and support levels. This model supports continuous revenue streams and enables regular feature updates, aligning with broader trends observed in the digital economy (McKinsey, 2023).

Value-Added Services and Bundling: Beyond core algorithmic offerings, many providers develop value-added services such as implementation support, user training, and customized dashboards. These services increase customer retention by embedding solutions more deeply into operational processes and creating long-term service relationships. This bundling strategy also helps differentiate offerings in a competitive and fragmented market (OECD, 2022).

Data Monetization and Platform Strategies: An emerging trend, particularly among small and medium-sized enterprises, involves platform-based models that aggregate and anonymize farm data to provide benchmarking and performance comparison tools. This approach creates additional revenue streams through data-driven insights and caters to growing market demand for cross-farm analytics, particularly in the context of sustainability benchmarking and productivity optimization (AgFunder, 2024).

Pursuit of Scalable, Low-Touch Advisory Services: Providers increasingly explore scalable solutions that minimize the need for intensive human support, such as API-based advisory services and automated decision-support modules. This model allows wider market reach with lower operational overhead, often coupled with premium service tiers for enterprise customers requiring customization or advanced support (McKinsey, 2023).

Investor Focus on Rapid Return on Investment (ROI): Access to venture capital and public funding frequently depends on business models that demonstrate financial viability and measurable impact within short timeframes, typically two to three years. Providers must therefore prioritize solutions that show clear economic or sustainability outcomes, such as yield improvements or cost reductions, to secure follow-on investment. However, fragmented data foundations and regulatory uncertainties remain significant barriers to scaling solutions beyond pilot deployments (Joint Research Centre, AI Watch).

These trends underscore the importance of stable and sustainable business models for AI DMST providers. They also highlight the need for policy frameworks that support innovation-friendly market conditions, address data governance challenges, and facilitate the development of viable business ecosystems. These considerations directly inform the strategic levers and recommendations presented in Chapter 6.

3.3.3 Power Concentration and Data Asymmetries

A recurring theme across interviews was the concentration of data and influence among a small number of large players - particularly machinery manufacturers and agro-chemical companies. These actors typically control proprietary data streams from on-farm sensors, connected machinery, or advisory services. Several respondents described a “closed ecosystem logic” in which tools and services are bundled tightly with hardware or product offerings, reducing the need - and often the possibility - for external tool integration.

This situation creates asymmetries not only in market power but also in innovation capacity. Stakeholders noted that access to high-resolution, annotated datasets is a critical enabler for AI development, but such data is often controlled by a few dominant actors. The workshop hypothesis stating that *“data portability and interoperability standards are key to reducing lock-in effects and supporting a competitive provider landscape”* received strong support (avg. score: **4.4**). A related hypothesis - *“public-sector support for shared technical infrastructure and standardization could help level the playing field for smaller providers”* - was also rated highly (avg. score: **4.5**).

3.3.4 Lock-in Mechanisms and Interoperability Challenges

Beyond data asymmetries, lock-in effects were described as a key barrier to market diversification. Equipment-linked software suites, proprietary interfaces, and vertically integrated service bundles limit farmers’ ability to adopt independent tools. Some respondents described scenarios where changing a decision-support tool would require replacing the machinery or reconfiguring the entire farm data environment.

Lack of standardized data formats and interoperable APIs further complicates integration across systems. While some progress has been made through open data initiatives, interviewees expressed concern that these efforts remain fragmented or voluntary. A minority of stakeholders also questioned whether public-sector actors were doing enough to coordinate or enforce interoperability measures. The idea of *“independent AI DMST evaluation or certification schemes to support better adoption decisions”* received moderate support (score: **3.8**), suggesting a need for further dialogue and exploration in this area.

3.3.5 Barriers for Smaller Providers

Startups, SMEs, and research institutions - many of which are responsible for early-stage innovation - face notable barriers to entering or scaling in the current market structure. Several respondents cited the lack of access to clean, annotated, and legally usable training datasets as a major constraint on developing robust AI models. This challenge was directly reflected in the hypothesis *“the lack of clean, annotated, and legally safe datasets is a primary technical barrier”* (score: **4.6**).

Computing infrastructure was also mentioned as a limiting factor. While cloud resources are theoretically available, smaller actors often struggle to finance or configure appropriate environments for training, testing, or deploying models. Shared computing environments or access to public infrastructure (e.g., AI Factories, see section 4.1) were seen as promising responses. The hypothesis *“shared computing infrastructure or on-demand access is needed to empower smaller actors”* received strong validation (score: **4.7**).

Legal uncertainty and the difficulty of navigating complex regulatory environments - such as the AI Act or Data Act - were also highlighted. Many stakeholders expressed a desire for more domain-

specific guidance, regulatory sandboxes, or learning frameworks to reduce perceived risks and compliance burdens.

3.3.6 Observed Innovation Bottlenecks

Several system-level bottlenecks emerged from the analysis. These include:

- Weak incentives to share data due to concerns about intellectual property, competitive advantage, and unclear licensing frameworks
- Fragmentation of standards, formats, and governance models across regions and sectors
- Limited trust in black-box systems, particularly for tools offering prescriptive or advisory recommendations
- A lack of comparability and quality assurance mechanisms, which makes it difficult for farmers to assess tool value or performance

Stakeholders also pointed to unclear return on investment (ROI) as a key adoption barrier. Particularly in the case of AI DMST still in pilot phases, the economic value of tools remains difficult to quantify. One interviewee noted that “many tools are technically promising, but the cost-benefit ratio is not visible to the farmer.” This aligns with the validated hypothesis that *“economic uncertainty and lack of ROI transparency are among the most critical barriers to AI DMST adoption”* (score: **4.6**).

3.3.7 Summary and Transition

The current market structure for AI DMST in agriculture privileges vertically integrated, resource-rich actors who can leverage proprietary data, infrastructure, and existing customer relationships. While this has enabled some innovation, it also creates significant barriers to entry for smaller providers and limits the availability of impartial, modular, and scalable solutions.

The dynamics outlined in this section highlight a need for policy mechanisms that address structural inequities - particularly around data access, interoperability, and shared infrastructure. This includes support for modular tool design, open standards, and strategic public investment in infrastructure where bottlenecks are clearly identified.

These considerations provide a foundation for the next section, which explores barriers to uptake and perceived failures in the current system from an adoption and demand-side perspective.

3.4 Adoption Barriers and Market Failures

3.4.1 Introduction and Framing

While the structural dynamics discussed in the previous section create enabling or constraining conditions for innovation, this section focuses on how these dynamics manifest as practical barriers to the adoption, trust, and sustained use of AI-enabled Decision-Making Support Tools (AI DMST) in agriculture.

Barriers to adoption can occur at multiple levels: from individual decision-making challenges (e.g. trust in AI outputs) to broader system-level issues (e.g. lack of incentives, infrastructure fragmentation). In parallel, several interviewees and workshop participants pointed to signs of market failure - for example, when technically promising tools fail to reach viable scale due to adoption barriers that cannot be solved by technological development alone.

3.4.2 Trust, Transparency, and Explainability

One of the most frequently mentioned barriers was a lack of transparency and trust in AI-generated recommendations. This concern was especially pronounced for advisory and diagnostic systems, where the stakes of a recommendation may be high, yet the reasoning behind it may be opaque. Several stakeholders described AI DMST as “black boxes”, noting that their outputs are difficult to interpret, verify, or contest.

The workshop strongly validated the hypothesis that *“lack of AI explainability and transparency reduces trust and acceptance among farmers”* (score: **4.7**). The absence of practical explainability mechanisms was seen not only as a technical challenge, but also as a source of user hesitation and resistance.

3.4.3 Economic Uncertainty and ROI Visibility

Economic considerations form another core barrier. Many farmers and advisors are uncertain whether investments in AI DMST will produce a clear or timely return. Interviewees described situations where costs - related to training, configuration, licensing, or infrastructure - were not justified by visible productivity or efficiency gains.

The hypothesis *“economic uncertainty and lack of ROI transparency are among the most critical barriers to AI DMST adoption”* was validated with a high average score of **4.6**. Several stakeholders called for tools or methods to support ROI assessment, either through simulation, benchmarking, or integration into existing planning tools.

3.4.4 Maturity, Fragmentation, and Practicality of Tools

The perceived immaturity of many AI DMST offerings was another cross-cutting issue. A significant number of tools are still in experimental or pilot stages, with limited field validation and restricted availability. This leads to fragmented offerings and a lack of standard reference points, making it difficult for farmers and advisors to assess quality or compare solutions across vendors and domains.

The hypothesis *“low perceived maturity and dominance of pilot-stage tools contribute to slow adoption”* received a strong score of **4.3**, with respondents noting that the visibility of stable, ready-to-use tools is low. While innovation is ongoing, the gap between proof-of-concept and practice remains substantial.

3.4.5 Administrative Burdens and Usability Challenges

Another frequently cited barrier relates to the operational burden associated with implementing and maintaining AI DMST. Stakeholders described tools that are time-consuming to set up, require manual data input, or do not integrate seamlessly with existing farm management systems. Especially for smaller farms, these usability issues can outweigh potential benefits.

Some interviewees also noted signs of digital fatigue - where the proliferation of tools and platforms leads to confusion, redundancy, or reduced motivation to adopt yet another solution. The lack of alignment with farmers’ daily workflows further compounds these challenges.

3.4.6 Perceived Bias and Lack of Impartiality

Concerns about impartiality and potential bias in AI DMST were also raised, particularly when tools are developed or deployed by vertically integrated actors. Some stakeholders worried that tool outputs might reflect commercial interests - e.g. favoring certain products, inputs, or machinery - rather than optimizing for user benefit.

The hypothesis that *“independent AI DMST evaluation or certification schemes would support better adoption decisions”* was discussed in the workshop and received moderate support (score: **3.8**). While the idea was seen as promising, several participants noted that effective implementation would require clear criteria, trusted institutions, and sector-wide agreement.

3.4.7 Summary and Cross-Cutting Observations

The barriers outlined in this section are diverse and interrelated. They span technical, economic, cognitive, and organizational dimensions, and they vary depending on the type of AI DMST, the agricultural domain, and the characteristics of the user base. For example, advisory tools based on generative AI face different adoption hurdles than operational tools embedded in machinery systems.

Several workshop participants noted that the lack of neutral, field-tested reference implementations contributes to user hesitancy. Reference deployments and clearer performance metrics could help bridge this gap.

Together, these barriers help to explain the relatively slow and uneven uptake of AI DMST in European agriculture, despite sustained innovation efforts and public investment. Addressing these challenges requires not only better tools, but also targeted support measures, transparency frameworks, and capacity-building.

The following section will explore opportunities for addressing these barriers - through both policy instruments and collaborative innovation models - and highlight potential enablers for a more inclusive, trusted, and effective AI DMST ecosystem.

3.5 Innovation Drivers and Ecosystem Opportunities

3.5.1 Introduction and Purpose

While much of the analysis thus far has focused on structural barriers and market dysfunctions, this section highlights a set of actionable opportunities that emerged across the interviews, desk research, and stakeholder workshop. These opportunities span technical, institutional, and infrastructural domains and reflect the collective insights of stakeholders who are actively shaping the future of AI DMST in agriculture.

Importantly, these enablers are not silver bullets. Many are still evolving and would require coordinated efforts, investment, and governance. However, if developed and implemented effectively, they have the potential to lower barriers, foster trust, and build a more inclusive and dynamic innovation ecosystem.

3.5.2 Technical Opportunities and Use Case Momentum

Several interviewees pointed to specific AI DMST use cases that show tangible promise and growing maturity. These include tools for crop stress detection using computer vision, variable-rate input optimization, and generative planning for crop rotation or irrigation scheduling. While not all of these are market-ready, stakeholders highlighted that certain niches are showing clear momentum.

A particularly strong signal came from the hypothesis *“low-cost AI DMST solutions using readily available devices (e.g., smartphones) can unlock adoption among small and medium-sized farms”*, which received a high validation score (**4.8**). This points to an opportunity for tools that are modular, mobile-accessible, and context-sensitive, rather than embedded in high-end, capital-intensive machinery systems.

In addition, lightweight AI models designed for edge computing - capable of operating in low-connectivity rural environments - were seen as a promising direction. The corresponding hypothesis (*“investment in edge-compatible, lightweight AI architectures”*) received a solid **4.3** in the workshop.

3.5.3 Shared Infrastructure and Data Ecosystem Development

Many stakeholders argued that sustained innovation requires not only tool development but also foundational infrastructure. This includes both technical and governance components of the data ecosystem.

The workshop strongly supported the hypothesis that *“publicly maintained data repositories with transparent licensing could improve trust and reduce redundancy in data collection efforts”* (score: **4.8**). Similarly, *“federated or sector-specific data spaces with stakeholder co-design”* received high validation (**4.7**), reflecting support for emerging projects like the Common European Agricultural Data Space (CEADS).

Interviewees also emphasized the need for modular, open-source pipelines, which refers to reusable software toolchains that allow developers to avoid re-building common data processing or machine learning workflows. Related infrastructure needs include domain-specific APIs - application programming interfaces tailored for agricultural use cases such as soil data retrieval or weather integration - and interoperability standards that ensure systems can communicate effectively across regions and technologies. The hypothesis *“data infrastructure investment is more critical than sensor hardware for unlocking long-term AI DMST value”* (score: **4.8**) captures this shift in thinking.

Together, these infrastructures were seen not only as technical enablers, but also as instruments of trust and participation, particularly for actors without access to proprietary datasets or systems.

3.5.4 Enabling Adoption Through Tool Framing and Positioning

Several interviewees stressed that how a tool is positioned - technically, communicatively, and economically - can make a significant difference for adoption.

One theme was the framing of AI DMST as supportive rather than prescriptive, which aligns with existing farmer practices and supports human-in-the-loop decision-making. The hypothesis *“positioning AI DMST as supportive increases likelihood of adoption”* received a moderate but clear signal (**4.0**).

Another strong insight concerned the visibility of economic value. Tools that help users assess potential benefits upfront were seen as critical. The hypothesis *“providing farms with tools to assess potential economic benefits of AI DMST could improve investment decisions”* received a high average score of **4.6**.

Stakeholders also emphasized the role of flagship projects - publicly supported, visible deployments of mature AI DMST that can create reference markets and demonstrate trustworthiness. This idea was highly validated (Hypothesis score: **4.8**).

Pull Factors for Adoption of AI DMST by Agrifood Practitioners

The adoption of AI-enabled Decision-Making Support Tools (AI DMST) by agrifood practitioners is primarily driven by four clearly evidenced motivations, identified through stakeholder interviews, workshop feedback, and validated hypotheses.

First, **economic benefits through cost savings** represent the most immediate and tangible driver. Farmers and agribusinesses adopt AI DMST to optimize resource use—such as fertilizers, pesticides, and feed—and improve labor efficiency. Real-world examples demonstrate input reductions of up to 30%, directly contributing to profitability. This factor was strongly validated by stakeholders, with cost control and economic return ranked among the highest adoption incentives.

Second, **support for regulatory and subsidy compliance** is a critical motivation. As regulatory frameworks such as the CAP eco-schemes introduce complex reporting requirements, practitioners increasingly rely on AI DMST to automate compliance tasks and secure access to subsidies. These tools help reduce administrative burdens and ensure that environmental and operational standards are met without excessive manual effort.

Third, **sustainability targets and market differentiation** play an important role in adoption decisions. AI DMST enable farms to align with EU sustainability objectives and respond to growing consumer demand for environmentally responsible products. By providing traceability and documentation capabilities, these tools facilitate access to premium markets and strengthen competitiveness through verified sustainable practices.

Fourth, **risk reduction and improved operational resilience** motivate the adoption of AI DMST to mitigate the impacts of climate variability, production risks, and market uncertainties. Predictive models and diagnostic tools support timely interventions, helping to stabilize yields and protect income. This driver was also highly rated in the hypothesis validation exercise, reflecting its critical importance in day-to-day farm management.

In addition to these primary motivations, several emerging factors are gaining relevance. These include access to new **revenue streams through carbon and biodiversity credit schemes, mitigation of labor shortages by automating repetitive or knowledge-intensive tasks, and operational simplification** through integrated digital platforms that reduce management complexity. While these factors were not the primary focus of this study, they represent important considerations for future adoption dynamics.

3.5.5 Institutional and Regulatory Innovation

Regulation is often portrayed as a brake on digital innovation, yet the policy packages now entering force in Europe also open new doors for AI-based AI DMST. Interviewees acknowledged that legal uncertainty has not disappeared, but they were equally clear that a wave of recent EU measures offers concrete advantages for agile developers and data-hungry applications.

The EU Data Act guarantees users the right to extract and share data generated by connected devices and related services. For agriculture this means that telemetry streams from tractors, sprayers or milking robots, locked inside proprietary clouds, must become portable on fair, reasonable and non-discriminatory terms.

The Data Governance Act and the forthcoming Common European Agricultural Data Space (CEADS) translate that legal right into operational reality. A federated trust framework, common

vocabularies and a model contract for data intermediaries will allow smaller firms to plug into a ready-made backbone instead of building bespoke data pipes.

One specific concern relates to the legal risks of using foundation models, especially those trained on datasets of unclear provenance. Several stakeholders noted that it is often not possible to verify whether the underlying data was legally sourced or whether all necessary rights (e.g., licensing, consent, traceability) were respected. This creates a hesitancy to engage with pre-trained models, even when such models could accelerate development or reduce costs. These concerns align with the requirements set out in the AI Act (see section 3.1.5), which emphasizes transparency, accountability, and lawful data usage in high-risk AI systems, underscoring the importance of clear data provenance and compliance throughout the AI development lifecycle.

The lack of legal clarity around responsibility, liability, and due diligence - that is, the obligation to carry out careful vetting and risk management when using third-party AI tools - discourages experimentation. Interviewees suggested that regulatory sandboxes, model-level documentation requirements, and clear compliance pathways could help reduce perceived risk and enable more confident innovation.

This view was reflected in the workshop, where the hypothesis “clearer, domain-specific regulatory guidance and sandbox environments could help innovators navigate legal requirements without fear of penalties” received a strong average score (**4.4**). Similarly, the hypothesis that “regulatory innovation (e.g., experimentation clauses) could reduce friction and enable more responsive, iterative adoption pathways” was validated at **4.6**.

Stakeholders also emphasized the need for capacity-building, particularly for smaller firms and non-commercial actors who often lack dedicated legal support. Investing in legal literacy, template contracts, or guidance tailored to agricultural AI could increase both innovation confidence and compliance levels.

3.5.6 Collaborative Innovation Models and Ecosystem Design

Innovation in AI DMST is not only a technical challenge - it is also a question of ecosystem coordination. Stakeholders across all groups emphasized the need for collaborative structures, such as:

- Public-private partnerships (PPPs) to create stable testbeds for real-world validation (Hypothesis: **4.2**)
- Multi-actor governance frameworks for a common data infrastructure
- Co-design processes involving not just developers but also farmers, advisors, and regulatory actors
- Integration of AI DMST with initiatives like AI Factories, GenAI4EU, and CEADS

Many respondents noted that the current innovation landscape remains fragmented, with duplication of efforts and a lack of common touchpoints. Strategic ecosystem design - focused on inclusivity, data sharing, and aligned incentives - was seen as essential for long-term success.

3.5.7 Summary and Outlook

The opportunities identified in this section highlight the breadth of levers available to improve the development and adoption of AI DMST. These include:

- Low-cost, modular, and explainable tools
- Shared data and compute infrastructure
- Regulatory clarity and legal risk mitigation
- Farmer-aligned framing and value demonstration
- Ecosystem coordination and public-private governance

While none of these enablers will resolve systemic challenges on their own, they represent pragmatic entry points for action. Many of them are already partially addressed by EU-level initiatives, which could serve as vehicles for coordinated intervention.

The next chapter synthesizes these insights into concrete policy recommendations aimed at enhancing the conditions for a competitive, trusted, and innovation-friendly AI DMST ecosystem in European agriculture.

4 Technical Requirements for AI DMST

Lifecycle demands, infrastructure needs, and scenario-based insights

4.1 Introduction and Scope

Understanding the technical requirements for developing and deploying AI-enabled Decision-Making Support Tools (AI DMST) in agriculture is essential to identifying enablers, barriers, and areas for targeted intervention. While many tools are conceptually promising, the feasibility of implementation depends heavily on the nature of the AI task, the quality and accessibility of input data, the required computing infrastructure, and the intended deployment environment.

The technical needs of AI DMST vary significantly depending on the agricultural domain, the class of AI DMST (e.g. operational, advisory), and the underlying AI technology (e.g. classical machine learning, computer vision, or generative AI). This chapter provides an overview of the AI lifecycle, discusses specific effort profiles along four representative use-case scenarios, and highlights common technical gaps encountered across the ecosystem. These observations are essential for evaluating the capacity of different actors - particularly SMEs - to contribute to innovation and adoption.

This section synthesizes insights from desk research, expert interviews, and the stakeholder validation workshop to identify key technical foundations required for AI DMST. It focuses on critical factors such as data sources, connectivity, compute infrastructure, and AI lifecycle requirements. The goal is to outline the enabling conditions and challenges that shape the development and deployment of AI DMST solutions across different technical scenarios.

4.1.1 AI Factories as Enabling Infrastructure

The European Commission introduced the concept of AI Factories to strengthen Europe's capacity for developing and deploying trustworthy, human-centric AI solutions. AI Factories are envisioned as shared infrastructure hubs that provide access to high-performance computing resources, curated datasets, regulatory sandboxes, and specialized support services.

In the context of AI-enabled Decision-Making Support Tools (AI DMST), AI Factories can play a critical role by:

- Reducing the high upfront costs of AI development for SMEs and research actors.
- Providing environments for safe experimentation, model fine-tuning, and compliance testing.
- Facilitating access to high-quality, annotated datasets relevant to agricultural applications.

- Offering legal and regulatory support to navigate AI Act requirements and data governance challenges.

AI Factories, beyond foundational AI research and large-scale model training, help close the gap between innovation and practical deployment - especially for domain-specific applications like AI DMST in agriculture. Their success will depend on ensuring broad accessibility, affordability, and alignment with sector-specific needs. This includes providing support for explainability, sustainability, and interoperability. To effectively serve agricultural AI DMST needs, AI Factories must support domain-specific model training environments tailored to the complexities of agricultural data and workflows. For startups, AI Factories offer the advantage of significantly reducing upfront infrastructure costs and accelerating development cycles by providing shared, compliant computing resources and expert regulatory support, thereby lowering barriers to market entry and fostering innovation.

4.2 AI Development Lifecycle in Agricultural AI DMST

The development of AI DMST typically follows a multi-stage lifecycle, each with distinct requirements and potential bottlenecks. The general sequence includes:

1. Data collection and preprocessing: Aggregating raw data (e.g. from sensors, public sources, farm management systems), cleaning it, and converting it into a format that is usable for model development.

2. Model training and validation: Selecting appropriate algorithms (e.g. classification, regression, generative), training them on annotated datasets, and tuning model settings to optimize performance.

3. Deployment and inference: Integrating the model into real-world systems and enabling inference in live environments (e.g. on-device, cloud, or hybrid).

Stakeholders consistently noted that data preparation is often the most effort-intensive step, sometimes accounting for a large share of the overall development time and cost. While this estimate is widely cited in AI literature, it was not explicitly confirmed in the stakeholder interviews conducted for this study. However, legal and technical barriers to data access, annotation, and interoperability were frequently mentioned as slowing down development.

While this general pipeline applies across most tools, the effort distribution and infrastructure demands can differ drastically depending on the AI DMST use case and model type.



Figure 1: Common lifecycle of AI systems

4.3 Scenario-Based Effort Profiles

To make the heterogeneity of AI-enabled Decision-Making Support Tools (AI DMST) more tangible, we model four archetype scenarios and estimate the technical effort, time and infrastructure each one typically requires along the AI lifecycle introduced in Section 4.2 (data preparation - model training - deployment). The aim is illustrative, not normative: the figures show relative magnitude and cost drivers so that readers can see where shared EU infrastructure or policy support might matter most. The effort classes are grounded in current supplier benchmarks and expert estimates; while actual projects may diverge, the relative spread between scenarios is robust.

The scenarios have been selected as they span the main diversity axes identified in the study so far:

- Decision horizon – operational (real-time) versus tactical (season-planning)
- Production context – crop and livestock applications
- AI approach – edge-vision, classical ML, large language models and time-series anomaly detection

These four use-case families scored highest for perceived relevance, investment interest and variety of technical requirements, giving a balanced lens on the AI DMST landscape.

Because no single dataset covers all relevant variables, the estimates combine expert judgement with publicly available benchmarks and other data sources rather than relying on exhaustive project analysis:

- Domain knowledge & stakeholder input: Technology providers and project teams provided indicative effort breakdowns and typical team compositions based on their experience.
- Public benchmarks & open projects: Data from publicly accessible machine learning benchmarks - such as model performance and resource usage reports published by platforms like Hugging Face - were used to inform assumptions about model sizes, hardware requirements, and inference speeds. These benchmarks provide standardized, comparable metrics from real-world AI models.
- Current price lists: Mid-2025 cloud computing tariffs (e.g., AWS, Azure, OVHcloud) and EU retail hardware prices were used as anchors for cost estimations.
- Internal sizing exercises: Standard productivity assumptions, such as labeling 1,000 to 1,500 images per engineer-day, were discussed and validated with technical experts.

The resulting tables therefore represent informed estimates, not prescriptive budgets; actual effort will vary by farm size, geography, data availability and team skill mix.

4.3.1 Scenario 1: Weed Detection Robot

This scenario describes the development and deployment of an AI-based vision system that enables farming robots to automatically detect and remove weeds. The goal is to reduce herbicide use and manual labor, supporting more sustainable and cost-efficient farming practices.

The system uses cameras mounted on robots to identify weeds among crops in real time. For this to work, the AI must be highly accurate under various field conditions - different lighting, soil types, and plant growth stages. It also needs to run on energy-efficient, embedded hardware directly installed on the robot.

Effort Breakdown:

1. Data Collection and Preparation

- To teach the AI what weeds and crops look like, around 50,000 to 100,000 field images must be collected and labeled.
- Labeling requires expertise: agricultural professionals are needed to correctly classify weeds and crop types, which is critical for the AI's accuracy.
- This phase typically involves 40–60 person-days of work and represents a significant portion of early development costs.

2. AI Model Development

- The AI model, based on image recognition techniques (e.g., using the YOLOv8 algorithm), is trained to recognize weeds from the labeled images.
- Model training can be performed either using high-end desktop hardware (e.g., an RTX 4090 graphics card) or cloud services (using industrial-grade GPUs like NVIDIA A100).
- Training typically costs €500 to €1,000 in cloud compute resources, or alternatively requires investment in local hardware (full system estimates to €4000 to €6000)

3. Deployment and Integration

- The trained AI model is installed directly onto the robot using compact, low-power processors (e.g., NVIDIA Jetson Orin).
- Engineers optimize the AI model to run efficiently on this hardware, ensuring real-time performance in the field.
- Hardware costs for AI processing units are around €3,000 to €8,000 per robot, depending on the level of onboard processing required.

4. Operational Costs

- Most costs after deployment come from maintenance and software updates rather than direct computing expenses.
- Field recalibration and updates to improve accuracy typically require 5–10 person-days per year.

Conclusion

This scenario shows that while the development of an AI-based weed detection system requires significant upfront investment - particularly in data preparation - it is still feasible for SMEs or startups operating in the agri-tech sector.

The most substantial barriers include the availability of high-quality, labeled image data and the need for extensive field testing to ensure robust performance under varying conditions. Public infrastructure initiatives, such as shared datasets and collaborative testing environments, could significantly reduce these entry barriers and promote faster innovation.

Key Needs: Access to shared, high-quality labeled image datasets; cost-effective hardware platforms for edge deployment; and standardized testing environments to accelerate field validation. Development is feasible for SMEs, but early-stage support for data and testing infrastructure is essential to lower costs.

Note: While current implementations of weed detection robots primarily rely on supervised learning and computer vision models, reinforcement learning is occasionally explored to improve autonomous navigation and adaptive control of mechanical actuators. However, due to high data and simulation requirements, RL remains largely experimental in this domain, with limited deployment in commercial field systems.

4.3.2 Scenario 2: LLM-Based Farm Advisory Assistant

This scenario describes the development of a chatbot (Chat-LLM) that provides farmers with tailored advice on regulatory compliance, best farming practices, and planning decisions. The tool uses Large Language Models (LLMs) - advanced AI models capable of understanding and generating human language.

Farmers can interact with the system by asking free-text questions, such as “What subsidies apply to my organic farm?” or “How should I rotate crops to improve soil health?” The AI advisor responds in natural language, pulling from a wide base of regulations, scientific research, and best-practice guidelines.

Because LLMs are highly complex models, the development focuses on two critical steps: fine-tuning an existing LLM for the agricultural domain, and ensuring that the system provides reliable, legally sound answers without “hallucinating” false information.

Effort Breakdown:

1. Data Collection and Preparation

- The AI needs to “learn” from carefully selected agricultural texts, EU directives, and national regulations.
- Assumption: Around 20 to 100 GB of text data - covering up to 100,000 documents - need to be collected and processed.
- Data cleaning involves removing duplicates, irrelevant information, and checking for proper licensing.
- This phase typically requires 30–40 person-days, including domain experts to ensure content accuracy and engineers to prepare the data for AI training.

2. AI Model Fine-Tuning (Estimated Effort: 1 – 2 weeks)

- Instead of creating a new language model from scratch, developers fine-tune an existing open-source model like Mistral-7B or LLaMA-2.
- Fine-tuning focuses on making the AI better at answering agricultural questions accurately and in line with legal requirements.
- This process uses powerful cloud-hosted GPUs (e.g., NVIDIA A100 or H100), requiring approximately 30–50 GPU-hours, which translates to €500–€2,000 in cloud compute costs.
- Alternatively, organizations with their own hardware can run this process locally, but it requires a machine with at least 48 GB GPU memory (e.g., RTX 6000 Ada Generation).

3. Deployment and Inference (Ongoing Costs)

- Once fine-tuned, the AI model is hosted in the cloud or on-premises servers.
- Typical usage patterns involve handling thousands of text-based queries per month.
- Inference (responding to each user query) costs are relatively low at around €0.0004 per 1,000 tokens, depending on the hosting setup.
- For typical advisory usage, inference costs remain low: answering around 1,000 farmer queries per month costs less than €1 when using open-source models and affordable EU-based cloud providers. Even large-scale deployments serving tens of thousands of queries remain well below €50 per month in direct AI computation costs.
- Hosting can be provided by EU cloud providers to avoid legal risks associated with non-EU data governance frameworks.

Conclusion

The main costs for this AI application arise during the data preparation phase, which demands significant manual effort to curate, clean, and properly license relevant agricultural content. While fine-tuning the AI model also requires considerable computing resources, these costs are typically lower than the human effort required to produce high-quality, domain-specific datasets.

Once deployed, operational inference costs remain moderate, making this a scalable solution for advisory services - provided that legal compliance and trustworthiness are ensured.

Key Needs: Transparent access to base models, infrastructure for safe fine-tuning and testing, and compliance support (e.g., legal guidance on data provenance and liability). Development is feasible with institutional or cloud-based support and requires clarity on licensing and responsibilities.

4.3.3 Scenario 3: Irrigation Planning Tool

This scenario describes the development of an AI-powered tool that helps farmers optimize irrigation schedules based on weather forecasts, soil moisture data, and crop types. The goal is to conserve water, improve crop yields, and reduce manual planning effort.

The tool is typically integrated into Farm Management Information Systems (FMIS) or mobile applications, enabling farmers to make informed decisions without needing advanced technical expertise. The AI models used here are lightweight, explainable, and focused on predicting water requirements for specific crops under varying environmental conditions.

Effort Breakdown:

1. Data Collection and Preparation

- The tool relies on structured data from weather services, soil moisture sensors, and irrigation logs.
- Typical data volumes are modest - about 0.5 to 2 GB of tabular data per growing season.
- Data harmonization involves aligning different data formats, handling missing values, and performing unit conversions.
- This phase typically requires 10–15 person-days, mainly for data engineering and ensuring compatibility with FMIS platforms.

2. AI Model Development

- The AI model typically uses simple, explainable techniques like decision trees or gradient-boosted trees (e.g., XGBoost).
- Training can be performed using standard office laptops or entry-level cloud virtual machines; no specialized GPUs are required.
- Model training takes less than one day and is often repeated periodically to improve accuracy with new data.
- This phase involves 4–6 person-days for model development, feature engineering, and testing.

3. Deployment and Inference (Ongoing Costs)

- The tool is typically deployed as a cloud-hosted web application or integrated into existing FMIS platforms.
- Inference is lightweight, allowing the model to run either in the cloud or directly on low-cost edge devices (e.g., Raspberry Pi) for offline operation.

- Ongoing inference costs are negligible, and most operational expenses stem from system maintenance and occasional retraining.
- Inference costs for this scenario are typically well below €10 per month, even for medium-sized farms.

Conclusion

This scenario demonstrates that AI-based irrigation planning tools can be developed with relatively low investment, making them accessible to SMEs and applied research groups. The main cost drivers are related to data preparation and integration into user-friendly platforms rather than AI model development or computing resources.

Public support for standardized weather and soil data APIs, as well as low-code platforms for easier user interface development, could further reduce costs and accelerate the adoption of such tools.

Key Needs: Access to standardized weather and soil data APIs, affordable cloud or edge-computing options, and user-friendly interface development frameworks. Development is feasible for small companies and research organizations with moderate technical expertise.

Key Needs: Access to standardized weather and soil data, model templates, low-code platforms for interface design, and testing environments with real user feedback. Feasible for many SMEs and applied research groups with moderate technical skills.

4.3.4 Scenario 4: Livestock Monitoring System

This scenario describes a future-oriented AI-based system for continuous monitoring of animal health and behavior through real-time sensor data. While parts of this concept are already in use - such as wearable sensors and cloud-based analytics - the deployment of advanced AI models directly on-farm, particularly on low-power edge devices, mostly remains experimental.

The goal of such a system is to enable earlier detection of health issues, stress, or abnormal behavior patterns, thereby improving animal welfare and productivity. By processing sensor data close to where it is generated, this approach aims to reduce latency for critical alerts and minimize dependence on constant cloud connectivity.

As of today, most AI inference still happens centrally (in cloud platforms or farm servers), but pilot projects are exploring lightweight anomaly-detection models that can run on edge gateways or embedded devices. This scenario illustrates what future livestock monitoring systems could look like as edge-computing capabilities mature.

Effort Breakdown:

1. Data Collection and Preparation

- The system collects continuous time-series data from sensors, typically generating 5–10 GB of data per herd per year.
- Labeling health events requires close collaboration with veterinarians to annotate instances of illness or stress in the historical data.
- This phase typically requires 25–30 person-days, including data synchronization, anomaly labeling, and balancing data for rare-event detection (illness is infrequent compared to normal behavior).

2. AI Model Development

- The AI typically employs time-series anomaly detection models, such as autoencoders or statistical threshold models, which are efficient and interpretable.
- Training is performed on moderate hardware, such as a workstation equipped with an NVIDIA RTX 4080 or equivalent; training time is typically 6–12 hours.
- This phase involves 5–7 person-days for model development, testing across multiple herds, and tuning sensitivity thresholds to minimize false alarms.

3. Deployment and Inference (Ongoing Costs)

- Data from sensors are typically pre-processed locally (e.g., filtering, basic threshold checks) using farm-installed gateways or low-power industrial PCs.
- However, AI model inference is most often performed centrally - either via cloud-hosted platforms or dedicated on-farm servers - to handle the computational load and ensure easier model updates.
- True on-device AI inference at the edge remains experimental and is generally limited to simple threshold-based alerts rather than full anomaly detection models.
- Cloud storage is used for aggregating data and conducting model retraining. Monthly cloud storage and compute costs typically range from €30 to €50 per farm.
- Regular system updates and calibration typically require 10–15 person-days per year.

Conclusion

This scenario illustrates the potential of AI-based livestock monitoring systems to improve animal health and welfare through early detection of anomalies. While data collection and cloud-based analytics are already common in commercial solutions, the deployment of advanced AI models directly on-farm, especially on edge devices, is still an emerging capability.

Significant research and pilot projects are underway to explore lightweight AI models suitable for edge deployment, but large-scale adoption will depend on further advancements in low-power hardware and reliable, explainable models.

Key Needs: Access to open sensor interfaces and standardized data formats; affordable, low-power edge-computing solutions; and practical validation environments for testing and improving model performance. Development is feasible for technology providers with expertise in IoT and time-series analytics, but scaling adoption will require building trust in system accuracy and demonstrating clear cost–benefit advantages.

4.3.5 Summary Note

The quantified figures demonstrate that while AI technologies for agriculture vary significantly in complexity, the primary barriers to adoption are not related to computing capacity, but rather to data availability, legal certainty, and the challenges of integrating AI solutions into highly diverse farming environments.

Simple tactical tools, such as irrigation planning systems, can often be developed with limited technical resources and modest investments, making them accessible even for smaller technology providers. In contrast, solutions involving advanced AI technologies - such as large language models or robotic vision systems - do not necessarily require the vast computational resources associated with training foundational AI models, but they do involve considerable effort in data preparation, domain adaptation, and system integration. While these upfront investments remain moderate in absolute terms, they can still represent a significant hurdle for smaller market actors when combined with regulatory uncertainty and limited access to validation environments.

This analysis highlights the need for support measures that go beyond providing raw computing power. AI Factories, as envisioned by the European Commission, can play a crucial role in lowering adoption barriers - not by offering high-end compute for foundational model development, but by providing affordable resources for smaller-scale model fine-tuning, testing environments, and, importantly, access to expertise and regulatory guidance. Their role in supporting compliance testing, knowledge exchange, and fostering best practices is just as critical as providing technical infrastructure.

Feasibility assessments should also carefully consider the specific characteristics of each use case. Some solutions can scale easily across regions and farm types, while others are highly dependent on local data conditions, farming practices, and technological maturity in specific sectors. For example, advisory tools based on LLMs can be adapted relatively quickly once high-quality content is available, whereas robotic solutions require intensive field testing and hardware adaptation for different farming environments.

A general feasibility ranking across stakeholder types (e.g., startups versus large corporates) oversimplifies the reality of agricultural innovation ecosystems. Feasibility is determined less by organizational size and more by access to domain-specific knowledge, high-quality data, technical expertise, and opportunities for real-world testing and validation. Future studies should therefore include a more granular analysis of these factors to guide targeted support measures and investment strategies.

4.4 Data Sources and Access Constraints

AI DMST draw from a broad and heterogeneous landscape of data sources, each contributing essential inputs for analysis, prediction, or recommendation. These include:

- Sensor data from fields and livestock (e.g., soil moisture, temperature, yield, animal health indicators)
- Farm management records, such as field history, input use, and crop rotations
- Remote sensing data, including satellite imagery and drone-based monitoring
- Weather forecasts and climate models, often combined with local sensor feeds
- Market and logistics data, capturing input prices, demand signals, and supply chain dynamics
- Expert knowledge and textual documentation, such as extension guidelines, research reports, and operational manuals

Despite this richness, accessing and using high-quality data remains one of the most persistent challenges in the AI DMST ecosystem. Stakeholders across interviews and the workshop highlighted a number of recurring constraints:

- A lack of clean, annotated, and legally safe datasets was cited as a major technical and legal bottleneck (Hypothesis validation score: **4.6**)
- Inconsistent data formats and a lack of interoperability across vendors and sources complicate integration
- Licensing ambiguity creates uncertainty about what data can be reused or shared, even in publicly funded projects
- Many publicly available datasets suffer from gaps in time, location, or resolution, reducing their practical usability

The evaluation workshop strongly validated the hypothesis that “publicly maintained data repositories with transparent licensing could improve trust and reduce redundancy” (score: **4.8**). This underscores the urgent need for structured public infrastructure to ensure data quality, legal clarity, and sustainable access - especially for smaller actors without proprietary datasets.

Agricultural Data Availability Specifics

In addition to the generic constraints above, agricultural data exhibits several domain-specific availability challenges that shape AI DMST development and uptake:

Sub-sector fragmentation. Sensor deployment and digital maturity vary widely across arable farms, livestock operations and specialty segments (e.g., viticulture), forcing AI DMST to support multiple data-ingestion and preprocessing pathways.

Licensing complexity. CAP-conditional data, GDPR requirements and divergent national agricultural policies lead to fragmented licensing terms, increasing legal uncertainty and slowing data sharing.

Infrastructure gaps. Many small- and medium-sized farms lack real-time IoT sensors due to cost, resulting in patchy field and livestock coverage that constrains model accuracy.

Annotation and quality deficits. Few publicly available datasets are fully annotated or standardized for machine learning; extensive cleaning and labeling overhead (Hypothesis H-3 scored 4.6/5) delays model training and deployment.

Interoperability shortfalls. The absence of sector-wide data ontologies and common APIs forces bespoke integration efforts, raising development costs and timelines.

4.5 Deployment Infrastructures and Connectivity Challenges

The infrastructure required to deploy and operate AI-enabled Decision-Making Support Tools (AI DMST) depends heavily on where and how these tools are meant to run. Each deployment strategy - edge, cloud, or hybrid - comes with specific technical and logistical implications.

4.5.1 Edge AI: Computing on the Farm

Edge-based AI DMST run directly on local devices, such as tractors, drones, or barn-installed sensors. These tools are especially useful in remote or low-connectivity areas but come with strict constraints:

- Models must support real-time inference and be optimized for low power usage
- This typically requires model compression, such as quantization or pruning, and compatibility with embedded systems
- Edge AI is often the only viable option in locations lacking stable internet connectivity

While technically demanding, edge deployment can provide farmers with fast, offline-ready tools - critical in time-sensitive operations like spraying or anomaly detection.

4.5.2 Cloud AI: Centralized Intelligence at Scale

Cloud-based AI DMST leverage the vast computing power of data centers to process information, train large models, and run complex tasks:

- Especially relevant for large-scale applications like LLM-based advisors or regional forecasting systems
- Enable coordination across multiple farms, devices, or business functions (e.g., logistics or market analysis)
- However, they introduce concerns around latency, connectivity dependence, and data transfer costs

The trade-off is clear: cloud systems offer power and scalability but are often inaccessible or unreliable in the field - particularly in underserved rural areas.

4.5.3 Hybrid Models: Bridging Farm and Cloud

Many real-world AI DMST solutions combine local and cloud resources:

- These hybrid architectures are common in tactical planning tools (e.g., for irrigation, fertilization, or feed management)
- They rely on secure, two-way data exchange between on-farm devices and cloud analytics systems
- Designing them requires strong interoperability and resilience to intermittent connectivity

This flexible model is promising but demands robust integration infrastructure - both technically and organizationally.

4.5.4 Connectivity: The Hidden Bottleneck

Across all deployment models, connectivity remains a major limiting factor. Many stakeholders pointed out that AI tools are only as useful as the sensor networks and wireless channels that feed them. Without reliable data streams, even the best-designed AI DMST cannot deliver consistent value.

Technologies like 5G, LoRa, and mesh networks are seen as important enablers - but their availability varies significantly across regions.

The study found broad support for infrastructure investment, especially in technologies that help level the playing field:

- The hypothesis *“Investment in edge-compatible AI architectures can improve deployment feasibility”* received solid validation (score: **4.3**)
- Even stronger support was found for *“Shared compute infrastructure for SMEs is needed to empower smaller actors”* (score: **4.7**)

4.5.5 Dependence on non-EU cloud providers

Many AI DMST solutions developed in Europe rely on cloud infrastructures operated by U.S.-based providers such as Amazon AWS, Microsoft Azure, and Google Cloud. These platforms offer advanced services for machine learning operations, scalable compute resources, and integrated data pipelines that are difficult to replicate with alternative providers. This reliance supports rapid development but also introduces long-term dependencies that affect both technical flexibility and data governance.

One concern is the growing dependency on proprietary tools and services offered by these platforms. Applications are often built using provider-specific environments and interfaces, making it costly and complex to transfer workloads to alternative solutions. Additionally, large volumes of data stored within these ecosystems create financial and logistical barriers to migration, as transferring data between providers can incur significant costs and operational disruptions.

Beyond technical considerations, the legal framework governing these cloud services also plays a critical role. Despite hosting data within the European Union, U.S. cloud providers remain subject to the U.S. CLOUD Act, which grants American authorities the right to access data held by U.S. companies, regardless of its physical location. This creates potential conflicts with European data protection regulations and raises concerns about data sovereignty and legal certainty for European users.

While these dependencies currently enable many AI DMST initiatives to scale efficiently, they also pose strategic challenges for long-term control over data, compliance with evolving regulatory frameworks, and the ability to transition to alternative infrastructures if needed.

4.6 System Integration and Explainability

Integration with existing systems - such as Farm Management Information Systems (FMIS), ERP tools, or digital platforms - is a precondition for tool usability. Fragmented software ecosystems and proprietary data standards currently limit the interoperability of many AI DMST.

Explainability remains a core technical and user-facing issue. Stakeholders emphasized that trust in AI DMST requires transparency at the point of inference. This is especially important for:

- Advisory systems using generative AI (e.g. LLM-based assistants)
- Diagnostic tools where false positives or negatives have high stakes

The hypothesis *“lack of AI explainability and transparency reduces trust and acceptance”* received one of the highest scores (**4.7**), underscoring the need for model documentation, user feedback loops, and interpretable output formats.

4.7 Summary of Technical Needs and Gaps

The analysis in this chapter highlights that the development and deployment of AI-enabled Decision-Making Support Tools (AI DMST) in agriculture face a diverse and highly fragmented set of technical and organizational challenges. These challenges vary significantly depending on the type of AI technology used, the deployment environment, and the targeted agricultural domain. A one-size-fits-all approach to infrastructure or policy support does not reflect the complexity observed in practice.

Across all scenarios, data preparation remains the most critical bottleneck in the AI lifecycle. Activities such as data cleaning, harmonization, annotation, and the legal vetting of training datasets consume the largest share of time and resources. This is especially true for applications requiring high-quality, annotated field data - often unavailable or locked in proprietary silos. Smaller actors, including start-ups and research institutions, face structural disadvantages in this area due to limited access to clean datasets, unclear licensing conditions, and the cost of legal compliance. These issues were consistently confirmed by stakeholder interviews and scenario-based effort profiles presented in this chapter. The effort and infrastructure demands differ considerably depending on the complexity of the use case:

- **Low-complexity scenarios** - such as mobile-accessible advisory tools based on lightweight machine learning models - are becoming increasingly feasible with open datasets, pre-trained models, and low-code development environments. These solutions typically require moderate computational resources and can often operate effectively in low-connectivity environments.
- **High-complexity scenarios** - including those based on foundation models, multimodal sensor fusion, or real-time edge-cloud integration - demand significantly higher investments in data quality, computational infrastructure, and compliance frameworks. These solutions are often beyond the reach of smaller firms and research initiatives without access to shared infrastructure or targeted public support.

A key insight from this chapter is that the current market and infrastructure landscape favors large, vertically integrated providers, who have both the resources to develop sophisticated AI models and privileged access to proprietary datasets. Without coordinated policy action, this imbalance is likely to widen, limiting innovation opportunities for SMEs and public research actors. These findings highlight the need for targeted infrastructure support and differentiated policy interventions.

5 Hypothesis Validation and Workshop Synthesis

Stakeholder-informed patterns and strategic implications

5.1 Introduction

The findings and recommendations of this study are grounded in a structured validation process combining multiple evidence sources. These include literature review, expert interviews with key stakeholders across industry, research, and policy domains, as well as a dedicated stakeholder workshop that gathered additional feedback and prioritization of key barriers and enablers.

Building on this qualitative evidence, a set of thematic hypotheses was developed and systematically validated. These hypotheses addressed critical factors influencing the adoption and scaling of AI-enabled Decision-Making Support Tools (AI DMST), covering areas such as data availability, regulatory conditions, business models, market demand, and infrastructure readiness.

The validation process involved assessing the relevance and confidence levels of each hypothesis based on stakeholder input. These assessments provided a robust foundation for identifying the most pressing systemic gaps, which are analyzed in the following section.

This structured approach ensures that the gap analysis and resulting policy recommendations are not only theoretically sound but also directly informed by the experiences and priorities of key actors in the field.

In addition to the stakeholder validation activities, the study also drew on an extensive review of relevant literature and policy documents. This desk research helped contextualize the qualitative insights and provided additional evidence on structural challenges and technological trends in AI adoption for agriculture.

5.2 Cross-Cutting Reflections and Themes

This section synthesizes the key structural challenges and recurring themes that emerged from the interview analysis, workshop discussions, and hypothesis validation. Rather than focusing on isolated technical issues, it highlights systemic barriers that cut across technological, economic, and regulatory dimensions of AI DMST adoption.

The goal is to provide a consolidated view of the most critical factors currently limiting innovation and market uptake. These reflections serve as a foundation for the subsequent identification of systemic gaps and the development of targeted policy recommendations.

Trust and Transparency as Preconditions for Adoption

A lack of trust remains a significant barrier to the widespread adoption of AI DMST. Stakeholders consistently emphasized that without transparent models, explainable outputs, and clear accountability, farmers and agricultural businesses are reluctant to rely on AI-driven recommendations.

Concerns over hidden biases in AI models and the risk of poor or harmful recommendations further reinforce the need for explainability and traceable decision logic.

Persistent Infrastructure and Data Access Challenges

While AI models themselves are becoming more technically accessible, the necessary data and infrastructure remain out of reach for many smaller actors. The cost and effort required to acquire, clean, and manage relevant datasets remain significant challenges, particularly for SMEs and co-operatives with limited resources.

Public data sources are often fragmented, lack critical metadata, or suffer from legal uncertainty regarding reuse. At the same time, private datasets remain locked behind commercial interests, limiting their broader utility for model development. These challenges do not always completely block innovation, but they often delay projects and increase financial and operational risks.

Uncertain Market Conditions and Weak Incentives for Adoption

The economic case for investing in AI DMST remains underdeveloped. Technology providers struggle to present reliable return-on-investment calculations, and many farmers remain cautious about adopting solutions without clearly demonstrated financial benefits.

This is particularly evident in the limited number of mature business models built around AI DMST solutions. Many tools remain in the pilot or prototype phase, with only a few achieving stable, recurring revenue streams. Market demand is concentrated on solving immediate and tangible farm-level challenges, while more advanced system-level solutions face difficulties scaling across regions due to differences in farming practices, data availability, and regulatory environments.

Regulatory Uncertainty as a Barrier to Innovation

A strong call emerged from stakeholders for greater clarity in the regulatory environment. While there is general awareness of upcoming policies like the AI Act and Data Act, many technology providers and adopters are unsure how these regulations will apply to their products and services.

This uncertainty results in delayed investments and product launches, as actors prefer to wait for clearer legal guidance before moving forward. The lack of dedicated regulatory sandboxes, where solutions can be tested in controlled environments, was repeatedly identified as a missed opportunity to accelerate innovation safely. Liability concerns further compound the issue, with unresolved questions about who is responsible when AI-driven decisions lead to financial loss or regulatory non-compliance.

Need for Structural Support to Lower Market Entry Barriers

The validation process revealed a clear demand for stronger enabling environments to support AI DMST innovation and lower entry barriers, particularly for smaller actors. Stakeholders emphasized the need for shared infrastructure to access high-quality data and develop AI models, as well as regulatory sandboxes that allow safe experimentation with new solutions. Dedicated funding mechanisms were also seen as essential to reduce market fragmentation and support early-stage initiatives.

While there was no explicit call for increased top-down governance, stakeholders highlighted the importance of policy frameworks that actively enable innovation rather than constrain it. Practical support structures—such as accessible testing environments, clear legal guidance, and incentives for cross-sector collaboration - are critical to help AI DMST solutions move beyond pilot phases and achieve scalable, real-world adoption.

5.3 Thematic Gap Analysis

Building on the evidence gathered through expert interviews, a stakeholder workshop, and the validation of key hypotheses, this section identifies four systemic gaps that currently impede the adoption and scaling of AI-enabled Decision-Making Support Tools (AI DMST) in European agriculture. These gaps span issues of data availability, market readiness, regulatory uncertainty, and technological infrastructure.

Each gap is directly linked to the real-world challenges described by stakeholders and substantiated by the study's validated hypotheses. The references shown in parentheses (e.g., H-03) correspond to specific hypotheses listed in Annex A 7.1, where detailed descriptions and validation scores are provided. This allows readers to trace each identified gap back to the underlying evidence base.

5.3.1 Gap 1 - Data Foundations

The foundation for AI-enabled decision-making in agriculture remains underdeveloped, particularly in terms of data availability, quality, and legal clarity. High-quality, annotated, and legally safe datasets are scarce (H-14), and incentives to create or share such datasets remain weak. While the concept of federated or sector-specific data spaces is well recognized (H-16), practical implementations are still limited. Publicly maintained repositories with transparent licensing could significantly improve trust and reduce redundant data collection efforts (H-15) yet remain underdeveloped.

In addition to these technical gaps, legal uncertainties around data ownership, liability for data misuse, and fears of model contamination or unintended consequences from reused models create strong disincentives for data sharing - even in publicly funded projects. These unresolved issues contribute to a reluctance to provide training-quality data, hindering innovation and slowing the development of robust AI DMST solutions.

Furthermore, there is currently no established data-AI value chain that enables seamless progression from data generation to model development and deployment. Fragmentation persists between different actors, technologies, and legal frameworks (H-17, H-18). A lack of clear business models for data monetization and value capture further reduces incentives for data sharing and investment in data quality. Without a functioning value chain and mechanisms to turn data into sustainable business opportunities, the availability and usability of high-quality datasets will remain limited.

Action Needs:

EU Level

- Define and enforce interoperability standards for agricultural data (H-17).
- Provide funding for the development of federated data spaces and trusted public repositories with transparent licensing (H-15, H-16).
- Establish legal frameworks and guidelines that clarify liability issues related to data sharing and model reuse, reducing legal uncertainty and the fear of liability for model contamination.
- Initiate research and innovation programs to explore sustainable data monetization models and strengthen the economic foundations of data sharing ecosystems.

Member States

- Implement national incentives for data sharing, including tax benefits or subsidies for high-quality, openly shared datasets.
- Provide legal advisory services and data governance support for SMEs and cooperatives to address liability concerns.
- Promote data literacy programs to help farmers and SMEs better understand data management, value creation, and the risks and rights associated with data sharing.
- Support the development of regional data hubs and co-design of sector-specific data spaces with local stakeholders (H-19).

Private Actors

- Contribute reference datasets under open licenses to public or sectoral repositories.
- Adopt common APIs and data models in product ecosystems to improve interoperability (H-18).
- Actively engage in the co-design of governance models for data spaces that address liability, data quality assurance, and model reuse risks.
- Explore and pilot new business models that capture the value of data products and services, helping to build a sustainable data economy.

5.3.2 Gap 2 - Adoption and Business-Model Viability

Despite growing technological capabilities, the adoption of AI-enabled Decision-Making Support Tools (AI DMST) in agriculture remains low. This is primarily driven by a lack of trust in AI solutions (H-1), insufficient business model clarity and limited transparency around return on investment (H-3), and the absence of visible economic benefits for end users (H-5). Farmers often perceive available solutions as immature or experimental (H-6), further slowing market penetration. Publicly supported flagship projects could provide important reference cases and showcase mature, trusted solutions to build confidence and drive adoption (H-7).

Additional barriers arise from the high investment requirements often associated with the deployment of AI DMST solutions. These investment needs manifest in various forms, including the acquisition of costly specialized hardware, expensive proprietary software licenses, and the reliance on expert knowledge and consultancy services for effective implementation and operation. Such costs create significant entry barriers, particularly for small and medium-sized farms, and limit broader market access. To overcome these barriers, promoting low-cost solutions that leverage readily available devices such as smartphones (H-10) remains essential. In parallel, the establishment of independent certification schemes (H-8) would help improve trust and guide purchasing decisions toward affordable and reliable solutions.

Beyond these directly validated barriers, the AI DMST ecosystem also suffers from significant market fragmentation and a lack of transparency. The market remains highly heterogeneous, shaped by a variety of technologies, actors, and agricultural sub-domains. This diversity limits the scalability of standardized solutions and complicates coordination across the ecosystem. Moreover, there is limited visibility into the roles of solution providers, platform intermediaries, and data holders, hampering the design of targeted policy interventions and coordinated innovation efforts.

Power asymmetries and platform dependencies create additional barriers to market entry for smaller actors, as lock-in effects around proprietary data and hardware ecosystems limit their ability to innovate and access end users (H-12, H-33). Without a more transparent and open market

structure, these dynamics risk further entrenching existing market leaders and reducing competitive innovation.

Action Needs:

EU Level

- Support the development of outcome-oriented business models for AI DMST through dedicated funding programs and innovation support (H-3, H-5).
- Establish and fund publicly supported flagship projects that demonstrate mature, high-impact AI DMST solutions across agricultural sub-sectors (H-7).
- Introduce transparency requirements for dominant market actors regarding data ownership and platform interoperability to reduce lock-in effects (H-12, H-33).
- Monitor market concentration trends through a dedicated observatory to inform timely regulatory interventions.

Member States

- Provide financial incentives, such as subsidies and risk-sharing schemes, to encourage early adoption of AI DMST, particularly for small and medium-sized farms (H-4).
- Facilitate independent certification programs for AI DMST to improve trust and guide purchasing decisions (H-8).
- Encourage national-level market transparency by requiring disclosure of major actors' roles and market positions, especially in critical sub-sectors.

Private Actors

- Develop explainable and transparent solutions clearly demonstrating economic benefits to end users (H-1, H-5).
- Create low-cost product variants tailored to the needs of small farms and resource-constrained users (H-10).
- Engage proactively in industry-led initiatives to promote interoperability and reduce platform dependencies (H-12).
- Increase transparency regarding data governance policies and business practices to support ecosystem-wide trust.

5.3.3 Gap 3 - Regulatory and Compliance Uncertainty

Uncertainty surrounding the implementation of the AI Act, Data Act, and sector-specific regulations creates significant adoption barriers for AI-enabled Decision-Making Support Tools (AI DMST) in agriculture. For many actors, navigating the evolving regulatory environment is complex and resource-intensive (H-26). A lack of clear, domain-specific regulatory guidance and sandbox environments inhibits experimentation and slows innovation (H-27, H-28).

These challenges affect small and medium-sized enterprises (SMEs) particularly hard. SMEs face significant concerns related to the unclear compliance obligations for "high-risk" AI systems under the AI Act and worry about their potential liability exposure when AI DMST outputs influence critical decisions such as plant protection or livestock feeding. Without clear guidance on documentation depth, risk classification, and liability management, SMEs are hesitant to bring AI DMST solutions to market.

Another critical bottleneck relates to intellectual property and copyright regulations. Copyright and database rights present hidden barriers for the development of AI models, particularly for computer vision systems trained on plant health images or for LLM-based advisory tools. The lack of clear, auditable provenance workflows makes it difficult for ag-tech startups to prove lawful use of training data, further increasing legal uncertainty and risk.

The upcoming Data Act offers opportunities to improve data availability and access but faces a “readiness gap” across the market. OEMs must prepare secure APIs for data sharing, and SMEs need to develop the capabilities to invoke their new data access rights effectively. Without standard API profiles and model contract clauses, the practical implementation of the Data Act is likely to be slow and fragmented.

Finally, current EU innovation funding mechanisms are sometimes seen as rigid and excessively focused on deliverables rather than real-world outcomes (H-29). This approach is particularly unsuited for the long development cycles and infrastructure-heavy investments required for economically viable AI DMST solutions. More flexible, long-term funding models (H-30) and investments in regulatory and legal capacity-building for agri-tech stakeholders (H-31) could help to help overcome these barriers and support the development of compliant, innovative solutions.

Action Needs:

EU Level

- Publish clear, sector-specific compliance guidelines and establish regulatory sandboxes to allow experimentation with AI DMST under real-world conditions (H-27).
- Accelerate the operationalization of the Data Act by publishing standard API profile requirements and model contract clauses for machine and sensor data well before its enforcement deadline.
- Address copyright and database rights barriers by establishing an EU-wide “TDM Opt-Out Registry” and publishing good practice handbooks to help SMEs demonstrate lawful training data usage.
- Monitor regulatory compliance burdens through a dedicated observatory and adjust support instruments based on evidence from the AI DMST sector.
- Reform EU funding programs to support more outcome-oriented, flexible, and long-term innovation investments (H-29, H-30).

Member States

- Facilitate national sandbox pilots and integrate experimentation clauses into their implementation of EU legislation (H-28).
- Provide advisory services to SMEs on regulatory compliance and liability management, particularly regarding AI Act risk classification and AI DMST liability exposure.
- Promote the use of standardized data access frameworks aligned with the Data Act and support the development of secure, interoperable data-sharing APIs.

Private Actors

- Proactively participate in regulatory sandboxes and contribute to the co-design of regulatory frameworks through industry platforms.
- Develop internal capabilities to manage data provenance and copyright compliance to mitigate legal risks.

- Prepare for the implementation of the Data Act by building API capabilities and exploring new data-driven business models that leverage expanded access rights.

5.3.4 Gap 4 - Infrastructure and Sovereignty

The development and deployment of AI-enabled Decision-Making Support Tools (AI DMST) in agriculture require robust, accessible, and sovereign digital infrastructure. However, current infrastructure remains fragmented, and critical gaps persist, particularly for small and medium-sized enterprises (SMEs). Shared computing environments and affordable, on-demand access to training resources are essential to empower smaller market actors (H-22), yet this infrastructure is often out of reach due to a lack of shared facilities and affordable, sovereign compute resources (H-23, H-24).

While the EU has made significant strides in promoting digital transformation, many agri-tech actors - especially SMEs - remain dependent on non-European cloud providers. Even when data centers are physically located within the EU, governance and legal control frequently remain with non-European corporations, raising concerns about data sovereignty and compliance with European legal standards (H-19). Reducing this dependency is crucial to protect sensitive agricultural data and maintain European competitiveness.

Beyond these structural gaps, existing policy instruments often fail to account for the highly heterogeneous infrastructure needs of AI DMST solutions. Infrastructure requirements vary significantly depending on the type of AI DMST, underlying AI architecture, and deployment scenario - whether cloud-based or edge-deployed, focused on inference or model training. However, when support schemes treat AI DMST as a homogenous category, applying one-size-fits-all funding and policy instruments do not align with the actual effort profiles and capabilities of different actors, the effectiveness of public investment is limited and highlights the need for differentiated, use-case-driven support mechanisms.

While compute infrastructure is widely acknowledged as a critical long-term enabler for AI DMST, most stakeholders - particularly start-ups and SMEs - did not identify compute access as an immediate barrier during the interviews and evaluation workshop. This is likely due to the widespread reliance on public cloud offerings provided by global hyperscalers. However, this reliance introduces hidden strategic risks related to vendor lock-in, cost escalation, and the lack of European control over essential data infrastructures. Without proactive investment in sovereign European alternatives, the AI DMST ecosystem remains exposed to long-term structural vulnerabilities.

The lack of interoperable interfaces and fragmented system architectures further hinders the seamless integration of AI solutions with farm environments (H-20). Investments in precompetitive infrastructure such as shared model hubs, open APIs, and standardized data resources would significantly accelerate innovation and support the development of sovereign, future-proof AI DMST solutions (H-25).

Action Needs:

EU Level

- Expand investments in shared compute resources (AI Factories) and establish precompetitive infrastructure to support model development and data sharing (H-24, H-25).
- Promote the development of sovereign European compute resources to reduce dependency on non-EU hyperscalers and ensure data sovereignty (H-19).
- Design differentiated, use-case-driven funding instruments that account for the varying infrastructure needs of different AI DMST deployment scenarios.

- Conduct a strategic review of cloud dependencies in agri-tech sectors and develop policy measures to mitigate long-term sovereignty risks.

Member States

- Support regional digital infrastructure projects focused on rural areas and foster public-private partnerships to expand sovereign cloud and edge-compute capabilities.
- Promote interoperability standards and open API frameworks to strengthen technological sovereignty and ensure seamless integration across farm systems.
- Provide targeted support measures for SMEs to access shared compute resources and overcome infrastructure-related barriers.

Private Actors

- Engage actively in the development and adoption of open interoperability standards (H-12).
- Invest in edge-compatible, lightweight AI solutions to reduce infrastructure dependencies and lower deployment costs for end users (H-21).
- Contribute to the creation of shared model hubs and collaborative training environments, supporting the development of open and accessible AI ecosystems (H-23).
- Conduct strategic assessments of current cloud dependencies and develop roadmaps toward more sovereign and resilient infrastructure solutions.

5.4 Summary

The identified gaps and corresponding action needs form a clear basis for targeted policy interventions and market support. Chapter 6 builds on these foundations by presenting concrete, prioritized recommendations for EU policy, designed to support both immediate action and long-term structural improvements in AI-enabled decision-making for European agriculture.

6 Recommendations

Proposed actions to support a competitive, trustworthy, and inclusive innovation ecosystem

6.1 Introduction

This chapter presents a set of policy recommendations derived from the preceding analysis of systemic gaps and barriers affecting the adoption and scaling of AI-enabled Decision-Making Support Tools (AI DMST) in European agriculture. These recommendations aim to support the development of a resilient, competitive, and innovation-friendly ecosystem that leverages the potential of AI technologies to advance sustainability, productivity, and economic resilience across the agricultural sector.

The analytical foundation of this report has highlighted critical interdependencies between data availability, market dynamics, regulatory frameworks, and technological infrastructure. Addressing these challenges requires a coordinated and strategic policy response that not only facilitates technological progress but also ensures public trust, supports fair market conditions, and safeguards European digital sovereignty.

The proposed recommendations are structured to provide actionable guidance for policymakers and relevant stakeholders, enabling them to address current obstacles while also preparing the ecosystem for future developments. Recognizing the need for both short-term impact and long-term resilience, the recommendations are organized into three clusters. The specified timeframes are indicative and serve as a general orientation for action initiation:

- **Immediate Actions (Within 24 Months):** Targeted interventions to address urgent barriers and create early momentum for adoption.
- **Medium-Term Interventions (2–5 Years):** Measures focused on strengthening the ecosystem through strategic investments, governance structures, and the development of shared resources.
- **Structural Changes for Long-Term Resilience (Beyond 5 Years):** Policy initiatives aimed at institutionalizing best practices, ensuring interoperability, and embedding AI DMST within broader European policy frameworks to secure long-term competitiveness and sovereignty.

In view of the dynamic nature of technological advancements and the evolving regulatory landscape, it is essential that these recommendations are implemented within a framework that allows for regular review and adaptation. Continuous stakeholder engagement will be critical to ensuring that policy measures remain aligned with market developments, technological capabilities, and societal expectations.

While this chapter focuses primarily on EU-level policy levers to ensure clarity and actionable guidance for European institutions, it also explicitly highlights where complementary actions by Member States, industry stakeholders, and research actors are essential to achieving the intended outcomes. These complementary actions are directly aligned with the policy measures proposed in each cluster and are presented alongside the respective recommendations to provide a comprehensive, coordinated perspective on implementation.

In the sections that follow, we outline the key systemic gaps once more to anchor the proposed solutions before presenting a detailed set of EU-focused policy.

6.2 Key Systemic Gaps and Strategic Levers

The policy recommendations outlined in this chapter are grounded in a detailed analysis of systemic gaps identified through literature review, expert consultations, and a hypothesis validation workshop (for detailed gap description see section 5.3). To ensure targeted and effective policy responses, this section briefly recapitulates these gaps, highlighting where EU-level intervention can create the highest leverage for impact.

The identified gaps are closely interconnected and overcoming them requires a coordinated application of strategic policy levers across four priority areas. The levers set out in this section are distilled from three complementary evidence sources developed earlier in the report: validated hypotheses in Section 5.3 and Annex 7.1, systemic gaps identified in section 5.3, and results from literature review in chapters 3 and 4.

6.2.1 Gap 1 - Data Foundations (G-1)

High-quality, interoperable, and legally secure datasets remain scarce, significantly limiting the development and deployment of AI-enabled Decision-Making Support Tools (AI DMST). Fragmented data governance, unclear licensing frameworks, and a lack of sustainable data-sharing models further exacerbate this issue.

Strategic Policy Levers (EU Level):

- Define and enforce interoperability standards for agricultural data to reduce fragmentation of data and systems.
- Provide dedicated funding for interoperable data spaces and trusted public repositories with transparent data licensing models.
- Establish legal guidelines clarifying liability and reuse conditions for shared datasets and AI models, reducing fears of model contamination.
- Support R&I programs exploring sustainable data monetization models to incentivize data sharing and value creation.

6.2.2 Gap 2 - Market Adoption and Business-Model Viability (G-2)

Adoption of AI DMST is hindered by low trust, limited visibility of economic benefits, and sometimes high initial investment requirements. The absence of transparent certification schemes and outcome-oriented business models further restricts market growth.

Strategic Policy Levers (EU Level):

- Launch publicly supported flagship projects to demonstrate the maturity and economic value of AI DMST solutions across diverse agricultural sectors.
- Develop or foster independent certification schemes to increase trust and transparency in the market.
- Provide financial incentives for early adoption through targeted EU programs, particularly for small and medium-sized farms.
- Introduce transparency requirements for dominant digital platforms to reduce market concentration and lock-in effects.
- Establish a market observatory to monitor adoption trends and competitive dynamics, informing future regulatory interventions.

6.2.3 Gap 3 - Regulatory and Compliance Uncertainty (G-3)

Complex and evolving EU regulations, including the AI Act and Data Act, create uncertainty for innovators and slow market entry. SMEs, in particular, face challenges in navigating compliance obligations and managing legal risks related to data usage and AI liability.

Strategic Policy Levers (EU Level):

- Publish clear, sector-specific implementation & compliance guidelines.
- Launch regulatory sandboxes for AI DMST experimentation under real-world conditions.
- Accelerate Data Act implementation through the development of standard API profiles and model contract clauses.
- Establish an EU-wide “Text and Data Mining (TDM) Opt-Out Registry” and publish best practice handbooks to reduce copyright and database rights barriers, facilitating lawful data mining across sectors. Agriculture-specific guidelines or registry components could be considered to address sector-specific challenges, while accounting for overlaps with other sectors.
- Reform innovation funding programs to support outcome-oriented, flexible, and long-term investment strategies aligned with the specific needs of AI DMST development.

6.2.4 Gap 4 - Infrastructure and Digital Sovereignty (G-4)

Dependence on non-EU hyperscalers and the lack of shared, sovereign compute resources pose strategic risks to Europe’s long-term competitiveness and digital autonomy. Infrastructure gaps are especially pronounced for SMEs in rural regions, limiting scalable deployment of AI DMST.

Strategic Policy Levers (EU Level):

- Expand investments in sovereign compute resources through AI Factories, ensuring these facilities are designed to accommodate the unique data, modeling, and deployment requirements of the agricultural sector, such as large-scale geospatial analysis, real-time sensor integration, and support for edge computing in diverse operational environments.
- Promote the development of precompetitive infrastructures such as shared model hubs, open APIs, and standardized datasets.
- Design differentiated funding instruments that reflect the varying infrastructure needs of different AI DMST deployment scenarios.
- Conduct a strategic review of cloud dependencies in the agri-tech sector and implement measures to mitigate long-term sovereignty risks.

These priority areas and policy levers form the foundation for the concrete recommendations presented in the next section. By addressing them in a coherent and sequenced manner, the EU can strengthen its leadership in responsible AI innovation while ensuring that European agriculture benefits from sustainable, competitive, and future-proof digital solutions.

6.3 Policy Recommendations

This section presents a focused set of policy recommendations derived directly from the validated gaps identified in Chapter 5. The proposed actions aim to strengthen the competitiveness, sustainability, and digital sovereignty of the European agricultural sector by accelerating the development and adoption of AI-enabled Decision-Making Support Tools (AI DMST).

The recommendations are structured across three clusters reflecting the expected implementation horizons:

- **Cluster A: Immediate Actions (≤ 24 months)** to remove critical barriers and initiate momentum.
- **Cluster B: Medium-Term Interventions (2–5 years)** to consolidate progress and address structural ecosystem needs.
- **Cluster C: Structural Reforms (> 5 years)** to ensure long-term resilience and strategic autonomy.

Disclaimer: The recommendations presented in this report are based on the independent analysis conducted as part of this study. They reflect the study team’s assessment of current challenges, stakeholder feedback, and potential policy responses. These proposals do not represent the official position or strategic goals of the European Commission or any EU institution. Furthermore, while care has been taken to ensure the relevance and plausibility of the measures, the study team acknowledges that it does not have full visibility into all existing policy instruments, legal constraints, or institutional boundaries. As such, the feasibility and implementation of each recommendation should be carefully assessed by the competent EU bodies before any further action is taken.

While the focus lies on EU-level policy levers, the effective implementation of these measures requires coordinated efforts from Member States and active engagement of industry actors. These complementary roles are outlined explicitly to support a coherent and collaborative approach.

6.3.1 Cluster A – Immediate Actions

EU-Level Action	Gap Addressed
A-1 Foster agricultural data interoperability via voluntary standards, public-private collaboration, and open APIs; legislate if required	G-1: Data Foundations
A-2 Fund public annotation tools and open agricultural data repositories to expand high-quality datasets, released under open licenses and compatible with CEADS.	G-1: Data Foundations
A-3 Publish an AI DMST compliance package and open sector sandboxes	G-3: Regulatory & Compliance Uncertainty
A-4 Co-fund flagship pilots that demonstrate certified (e.g., in collaboration with agrifoodTEF), explainable AI DMST and use outcome-driven grant modalities	G-2: Market Adoption & Business Models
A-5 Mobilize the agrifood focused AI Factory IT4LIA for SMEs via a voucher scheme	G-4: Infrastructure & Sovereignty

Complementary actions: To support the successful implementation of immediate EU-level measures, coordinated actions from **Member States (MS)** and **industry** stakeholders are recommended:

[MS] Co-finance the development of regional data hubs and promote the integration of national data sources into CEADS (*supports A-2*).

[MS] Provide advisory services and capacity-building programs to help farmers, SMEs, and co-operatives manage regulatory compliance, data governance, and liability risks (*supports A-3*).

[MS & Industry] Facilitate open innovation environments, including living labs and regional test environments, to enable experimentation with AI DMST solutions (*supports A-3, A-4*).

[Industry] Align product development roadmaps with emerging EU interoperability standards and contribute to the design and adoption of open API frameworks (*supports A-1*).

[Industry] Provide high-quality, openly licensed datasets to public repositories or develop sustainable data monetization models to strengthen the sector's data value chains (*supports A-2*).

A-1 Foster Agricultural Data Interoperability

Access to high-quality, well-structured data is still one of the biggest hurdles for AI solutions in agriculture. Accordingly, the EU should promote the development and widespread adoption of common technical standards covering critical data domains such as soil conditions, weather observations, crop yields, and machine telemetry.

Early action should prioritize voluntary public–private frameworks and targeted support measures, such as interoperability testbeds, open-source reference APIs, harmonized metadata vocabularies, and the designation of relevant High-Value Datasets (HVDs) - i.e. datasets having considerable socio-economic benefit and therefore are subject to enhanced availability requirements. These instruments would facilitate seamless data exchange across the sector.

If voluntary measures do not deliver the required level of interoperability, legislation could be introduced to set baseline requirements and address persistent fragmentation. This graduated approach balances flexibility with regulatory certainty, easing integration and lowering barriers for equipment manufacturers, software developers, and farmers.

A-2 Fund Public Annotation and Repository Services

AI models depend on large volumes of well-prepared data, yet such datasets remain scarce for many agricultural use-cases. The EU should therefore establish dedicated funding to create high-quality public data repositories and annotation services that simplify dataset preparation and labelling.

Support should prioritize existing gaps - for example, data on under-researched crops, regional climate impacts, and sustainable farming practices. Projects financed under this action should release their datasets under open licenses and ensure full technical compatibility with the Common European Agricultural Data Space (CEADS), thereby maximizing reuse and accelerating AI DMST development across the sector.

A-3 Provide Compliance Guidance and Open Sandboxes

Many small companies struggle to navigate the complex requirements of the AI Act and the Data Act. This slows down innovation and market entry. To reduce these barriers, the EU should offer clear, practical compliance guidelines specifically for the agricultural sector.

Additionally, regulatory sandboxes - safe testing environments - should be created to help innovators try out new AI solutions in real-world settings without the immediate pressure of full compliance. These sandboxes could focus on important use cases like crop monitoring, livestock welfare, and greenhouse automation. SMEs should be supported with vouchers or consultancy services to help them participate.

A-4 Demonstrate and Scale Mature AI DMST Solutions

Farmers are often hesitant to adopt new digital tools because many solutions seem experimental and lack clear economic benefits. To change this perception, the EU should support (large-scale) demonstration projects that show the practical and economical value of certified, explainable AI solutions in everyday farming operations.

These projects should be linked to real business outcomes - such as reducing fertilizer use or improving profitability - and funding should be provided based on achieving these outcomes. A staged funding approach could help ensure that only the most promising solutions move from pilot phase to wider deployment.

A-5 Improve SME Access to the Agri AI Factory

Although the EU has launched an agriculture-focused AI Factory (IT4LIA), many small businesses remain unaware of its existence or lack the means to benefit from its services. A voucher scheme, coupled with a streamlined, centralized application process, could give SMEs affordable access to expert support, computing resources, data-preparation tools and compliance testing.

To better address sector-specific needs, the AI Factory could offer a tailored set of agri-specific resources, such as:

- Curated agronomic datasets (e.g., crop phenotyping, soil data, regional weather time series) in CEADS-compatible formats.
- Domain ontologies and common vocabularies to support semantic interoperability.
- Simulation or digital-twin environments to test models under realistic farm conditions.
- Edge-deployment testbeds compatible with common agricultural machinery and sensors.
- Regulatory sandboxes aligned with CAP and AI Act requirements for risk, transparency, and robustness assessments.
- Bundled advisory support from agronomic, technical, and legal experts.

Such a targeted offering could significantly lower entry barriers for SMEs and help accelerate the development of competitive AI DMST in the agri-food sector.

6.3.2 Cluster B – Medium-Term Interventions

EU-Level Action	Gap Addressed
B-1 Embed a certified-AI DMST bonus into future CAP eco-schemes	G-2: Market Adoption & Business Models
B-2 Expand AI Factories and co-fund open license agri foundation models	G-1: Data Foundations & G-4: Infrastructure
B-3 Establish an EU AI DMST Observatory for responsive monitoring	G-3: Regulatory Alignment & G-4: Compute Risk

Complementary actions: To strengthen the impact of medium-term policy actions, the following contributions are encouraged:

[MS] Align national CAP Strategic Plans with EU-level incentives by introducing additional financial rewards for the use of certified AI DMST, especially targeting small and medium-sized farms (*supports B-1*).

[Industry] Actively participate in voluntary certification schemes and contribute to the demonstration and scaling of certified, explainable AI DMST solutions (*supports B-1, B-2*).

[Industry] Explore and implement sustainable data-sharing and monetization models that promote broader access to AI solutions and support the long-term viability of the data economy (*supports B-2*).

B-1 Include a Certified-AI DMST Bonus in Common Agriculture Policy (CAP) Eco-Schemes

To create a lasting incentive for using AI tools in farming, the EU should integrate certified AI solutions into future CAP eco-schemes. Farmers who use certified decision-support tools that help reduce inputs like fertilizers or pesticides could receive additional payments per hectare.

This would reward sustainable farming practices while also driving demand for high-quality AI solutions. Verification could be handled through the reporting functions already built into certified tools, reducing administrative effort.

B-2 Expand AI Factories and Develop Open Foundation Models

Europe needs to strengthen its digital sovereignty and reduce its reliance on external AI technologies. One way to achieve this is by expanding the AI Factory network to more regions and supporting the development of open, agriculture-specific AI foundation models.

The foundation models envisaged here should be tailored to the unique requirements of the agri-food domain. Exemplary key characteristics could include:

- **Multi-modal training data:** integration of satellite imagery, drone observations, in-field sensors, and textual agronomic knowledge to capture the full production context.
- **Fine spatio-temporal granularity:** ability to model seasonal, regional and micro-field variations relevant to European cropping systems.

- Embedded weather and climate signals: incorporation of meteorological and climate-projection data for forward-looking decision support.
- Multilingual and domain-specific vocabulary: coverage of EU languages and specialist agricultural terminology to ensure accessibility for diverse user groups.
- Edge-efficient architectures: parameter efficiency and compression techniques that permit deployment on resource-constrained devices (e.g. tractors, drones, mobile apps).
- Built-in explainability and compliance hooks: model outputs accompanied by provenance metadata and risk-assessment primitives aligned with forthcoming AI-Act requirements.

Developing such models within the AI-Factory framework would help European actors share compute resources, reference datasets and evaluation pipelines, while ensuring that resulting models remain openly available for adaptation across the agri-food value chain.

B-3 Establish an EU AI DMST Observatory

To ensure that policy remains aligned with market realities, the EU should create a dedicated observatory to monitor the development and adoption of AI decision-support tools. This observatory would provide regular reports on technology uptake, market dynamics, and potential bottlenecks in areas such as computing resources and reliance on non-EU technology providers.

By identifying emerging risks early, policymakers would be better equipped to adapt funding programs and regulatory frameworks to support the sector's long-term resilience.

6.3.3 Cluster C – Structural Reforms

EU-Level Action	Gap Addressed
C-1 Review current legal duties (see section 3.1.5) and, if interoperability gaps persist, develop sector guidelines or a standardization mandate to ensure open-API access to agricultural equipment data	G-1: Data Foundations & G-2: Market Structure
C-2 Co-finance a multi-country rural edge-cloud backbone, e.g., under CEF-Digital, leading to sustainable and trusted structures	G-4: Infrastructure & Sovereignty

Complementary actions: To enable the successful implementation of long-term reforms, the following actions are recommended:

[MS] Co-finance and participate in the governance of rural edge-cloud infrastructure to ensure national priorities and local connectivity needs are addressed (supports C-2).

[Industry] Develop and adopt modular, open API solutions that foster interoperability across platforms and reduce vendor lock-in (supports C-1).

C-1 Review and Mandate Open API Access if Needed

Although the Data Act strengthens user rights to obtain machine-generated data, it does not by itself guarantee that agricultural equipment will expose those data through open, standardized APIs. To prevent residual interoperability barriers, the Commission should (i) monitor market behavior under full existing legislation (see section 3.1.5) and (ii) assess whether further measures are required.

C-2 Co-Finance a Rural Edge-Cloud Backbone

To guarantee long-term digital sovereignty and ensure that rural areas are not left behind, the EU should co-finance a dedicated rural edge-cloud infrastructure. This network of small, decentralized data centres would provide fast, low-latency access to AI services, helping farmers and rural businesses take full advantage of digital innovations.

Such investments would also support broader EU goals for rural development and sustainable growth, ensuring that all regions benefit from the digital transition.

6.4 Outlook and Closing Remarks

6.4.1 Wrap-Up of the Study's Main Insights

This study validated four systemic gaps - data foundations, market adoption, regulatory clarity, and infrastructure sovereignty - that slow the uptake of AI-enabled Decision-Making Support Tools (AI DMST) in European agriculture (see chapter 5). The ten recommendations in Chapter 6 form a coherent response: they tighten interoperability rules, unlock high-value data, lower compliance costs, showcase mature solutions, and build sovereign compute capacity. These proposals stem from an independent research project; they do not represent official EU policy and will require further feasibility checks by the competent institutions.

6.4.2 Future Scenarios: With vs. Without Intervention

If no decisive action is taken, Europe risks persistent data silos, slow farmer uptake, widening dependence on non-EU hyperscalers, and lost ground on Green Deal targets. SMEs providing AI-based solutions will face higher entry barriers, while fragmented standards will continue to erode trust.

With the recommended measures in place, the Union could achieve an interoperable agricultural data space, a vibrant provider SME ecosystem, and a secure edge-cloud backbone that keeps sensitive data under European jurisdiction. Certified AI DMST could deliver measurable cuts in input use, emissions, and production costs, helping the sector progress toward climate-smart farming.

6.4.3 Open Issues Requiring Further Evidence

Despite broad stakeholder consensus, several questions remain open:

- **Impact evidence** – robust, farm-level data on yield and efficiency gains, profitability, and environmental benefits from AI DMST are still scarce.
- **Compute bottlenecks vs. sovereignty risks** – current interviews suggest access to computing capabilities (mostly provided by US provided hardware) is less urgent than long-term dependence on external providers; the balance needs regular re-assessment.
- **IP and liability** – the legal footing for reusing multimodal data (images, sensor streams, text) in already-trained AI models remains unsettled, particularly for foundation-model fine-tuning. This issue intersects with several EU frameworks on intellectual-property and liability- such as the Copyright and Database Directives, the Trade Secrets Directive, and forthcoming AI-specific liability legislation - whose practical implications for AI DMST warrant further analysis.

6.4.4 Priority Areas for Future Research and Monitoring

To close these gaps, the following evidence-building activities are recommended:

- Periodic **farm-level uptake surveys** to quantify adoption rates, user profiles, and perceived barriers.
- A living **map of the provider landscape and value chains**, updated at least annually, to spot market concentration or capability gaps.
- **Indicator dashboards** that track GPU hours, chip import trends, and hyperscaler expenditure, flagging any emerging dependency risks. The planned AI DMST Observatory (Recommendation B-3) can coordinate these data streams and feed them into adaptive policy cycles.

6.4.5 Cross-Sector and Global Linkages

Agricultural AI DMST will not evolve in isolation. Many building blocks - edge-cloud infrastructure, data-sharing standards, AI assurance methods - overlap with manufacturing, health, and environmental data spaces. Aligning technical frameworks and governance models across sectors reduces duplication and boosts Europe's bargaining power in global standard-setting bodies (ISO, FAO digital codes). Synergies with the EU's Climate Tech and Net-Zero agendas can further amplify impact and funding efficiency.

6.4.6 Final Reflection and Call for Adaptive Governance

Europe may not yet lead in training the largest foundation models, but it can become the world's reference region for responsible, high-impact AI in agriculture. Achieving that status demands

flexible instruments that evolve with empirical evidence and technology progress. Continuous dialogue among EU institutions, Member States, industry, and the research community will be essential to refine rules, redirect funds, and scale what works. By staying adaptive - and by acting now - the Union can ensure that AI DMST become a cornerstone of sustainable, resilient, and globally competitive European food systems.

Note: International competitiveness issues (e.g. Europe's reliance on non-EU cloud and hardware suppliers, or China's state-led deployments) were discussed during the study. Given limited empirical evidence and the focus on levers under immediate EU control, no specific recommendation is formulated here. Strategic dependencies are instead flagged in section 3.1.5 and will require ongoing monitoring as the policy landscape evolves.

7 Annex

7.1 List of Validated Hypotheses

This annex presents the full list of hypotheses that were developed and tested as part of the study's stakeholder validation process. The hypotheses reflect key assumptions about barriers, enablers, and structural characteristics of the AI-enabled Decision-Making Support Tools (AI DMST) ecosystem in agriculture.

Each hypothesis was evaluated by stakeholders during the expert workshop and rated on a scale from 1 (**strongly disagree**) to 5 (**strongly agree**), based on their professional experience and sectoral perspective. The scores represent the **average rating** received across all responses and are grouped thematically to reflect the main areas of analysis in the report.

These scores are not intended as definitive judgments, but rather as indicative insights into stakeholder perceptions. They complement the qualitative findings presented in the main report and provide a structured basis for identifying areas of consensus, divergence, and future inquiry.

7.1.1 Uptake, Adoption & Economic Barriers

- H-1: Lack of AI explainability and transparency reduces trust and acceptance of AI DMST among farmers. (Score: 4.7)
- H-2: Positioning AI DMST as supportive rather than prescriptive increases the likelihood of adoption. (Score: 4.0)
- H-3: Economic uncertainty and lack of ROI transparency are among the most critical barriers to AI DMST adoption. (Score: 4.6)
- H-4: Financial support mechanisms (e.g., subsidies, risk-sharing models) can significantly boost adoption if targeted and well-structured. (Score: 4.1)
- H-5: Providing farms with tools to assess potential economic benefits of AI DMST could improve investment decisions and uptake. (Score: 4.6)
- H-6: Low perceived maturity and dominance of pilot-stage tools contribute to slow adoption of AI DMST in agriculture. (Score: 4.3)
- H-7: Publicly supported flagship projects showcasing mature AI DMST could accelerate uptake by creating visible reference markets. (Score: 4.8)
- H-8: The establishment of independent AI DMST evaluation or certification schemes would support better adoption decisions. (Score: 3.8)

7.1.2 Market Structure & Innovation Dynamics

- H-9: Public-private partnerships can reduce time-to-market for promising AI DMST innovations and create stable testbeds for real-world validation. (Score: 4.2)
- H-10: Low-cost AI DMST solutions using readily available devices (e.g., smartphones) can unlock adoption among small and medium-sized farms. (Score: 4.8)
- H-11: Market concentration is emerging in specific AI DMST domains, particularly in capital-intensive sectors like animal production. (Score: 3.6)
- H-12: Data portability and interoperability standards are key to reducing lock-in effects and supporting a competitive provider landscape. (Score: 4.4)

- H-13: Public-sector support for shared technical infrastructure and standardization could help level the playing field for smaller providers. (Score: 4.5)

7.1.3 Data Foundations, Data Spaces & Infrastructure Readiness

- H-14: The lack of clean, annotated, and legally safe datasets is a primary technical barrier for the development of robust AI DMST. (Score: 4.6)
- H-15: Publicly maintained data repositories with transparent licensing could improve trust and reduce redundancy in data collection efforts. (Score: 4.8)
- H-16: Federated or sector-specific data spaces with stakeholder co-design can create usable frameworks for secure and incentive-aligned data sharing. (Score: 4.7)
- H-17: The absence of standardized and interoperable data infrastructure limits the scalability and integration of AI DMST in agriculture. (Score: 4.0)
- H-18: Public support for modular, open-source data pipelines and interfaces could accelerate the deployment of scalable AI DMST infrastructure. (Score: 4.1)
- H-19: Data infrastructure investment (regional data hubs and domain-specific APIs) is more critical than sensor hardware for unlocking long-term AI DMST value. (Score: 4.8)

7.1.4 Computing, Integration & Shared Investments

- H-20: Lack of interoperable interfaces and fragmented system architectures are major blockers for the integration of AI DMST into farm environments. (Score: 4.1)
- H-21: Investment in edge-compatible, lightweight AI architectures can increase adoption in field-deployed agricultural applications. (Score: 4.3)
- H-22: Shared computing infrastructure or on-demand access to training environments is needed to empower smaller actors to develop and refine AI DMST. (Score: 4.7)
- H-23: The creation of (shared) foundational AI models in agriculture requires shared infrastructure and cannot be sustained by single actors. (Score: 4.2)
- H-24: Publicly supported AI factories can lower entry barriers for developing robust, domain-specific models. (Score: 4.1)
- H-25: Investment in precompetitive infrastructure (e.g., shared training data, compute environments, model hubs) would significantly accelerate innovation. (Score: 4.6)

7.1.5 Regulatory Frameworks & Innovation Support

- H-26: Uncertainty around regulatory requirements (e.g., AI Act, Data Act) increases perceived risks and slows down AI DMST adoption in Europe. (Score: 4.2)
- H-27: Clearer, domain-specific regulatory guidance and sandbox environments could help innovators navigate legal requirements without fear of penalties. (Score: 4.4)
- H-28: Regulatory innovation (e.g., experimentation clauses) could reduce friction and enable more responsive, iterative adoption pathways. (Score: 4.6)
- H-29: Current EU innovation funding mechanisms are seen as inefficient due to excessive focus on deliverables rather than outcome-oriented R&D. (Score: 3.7)
- H-30: More flexible, long-term funding models would better support iterative development, deep-tech experimentation, and infrastructure for AI DMST. (Score: 4.5)
- H-31: The EU should invest in regulatory and legal capacity-building for agri-tech stakeholders to support confidence and participation. (Score: 3.7)

7.1.6 Market Conditions & Gaps

- H-32: European policy should prioritize enabling data access and reuse (especially in agriculture) over imposing compliance-heavy obligations. (Score: 4.8)
- H-33: Targeted regulation to support interoperability and fair access could prevent market concentration and reduce lock-in risks. (Score: 4.0)
- H-34: Greater emphasis on market-enabling regulation (e.g., standard APIs, interoperability mandates) would improve access and stimulate competition. (Score: 4.4)
- H-35: Regulatory innovation (e.g., experimentation clauses, flexible compliance models) could help reduce friction and improve adoption in agriculture. (Score: 4.3)

7.2 Glossary

Term	Definition
AI	Artificial Intelligence - the simulation of human intelligence processes by machines, especially computer systems.
AI DMST	AI-enabled Decision-Making Support Tools - digital tools that leverage artificial intelligence to support decision-making in agriculture.
API	Application Programming Interface - a set of rules and tools for building software and enabling different systems to communicate.
CAP	Common Agricultural Policy
CEADS	Common European Agricultural Data Space - an EU initiative to enable trusted data sharing in the agricultural sector.
CEF	Connecting Europe Facility
CNN	Convolutional Neural Network - a type of deep learning model used especially for image recognition and computer vision tasks.
Chat-LLM	A large language model optimized for conversational interfaces, enabling AI DMST tools to process natural-language queries and provide interactive, context-aware recommendations.
DG CNECT	Directorate-General for Communications Networks, Content and Technology
EDIC	European Digital Infrastructure Consortium
EDIH	European Digital Innovation Hub - EU-supported centers providing access to technology, infrastructure, and expertise for SMEs and public institutions.
Edge AI	AI applications that run on local hardware (e.g. sensors, robots) rather than centralized cloud infrastructure.
EU	European Union.
FAO	Food and Agriculture Organization of the United Nations
FMIS	Farm Management Information System - digital platforms that support planning, monitoring, and documenting farming operations.
GPT	Generative Pre-trained Transformer - a class of language models used in generative AI, such as OpenAI's GPT series.
GPU	Graphics Processing Unit - specialized hardware for processing large amounts of data, especially useful in AI training and inference.
HVD	Datasets formally identified by the European Union as having significant socio-economic importance, making them critical for innovation and policy development. Under the EU's Open Data Directive, HVDs are subject to enhanced accessibility and interoperability requirements to ensure they can be widely reused.
IoT	Internet of Things - interconnected sensors and devices that collect and exchange data over the internet.
ISO	International Organization for Standardization
LLM	Large Language Model - a type of AI model trained on large text datasets to generate human-like language and reasoning.
ML	Machine Learning - a subset of AI where algorithms learn from data to make predictions or decisions.
MS	Member States
ROI	Return on Investment - a measure used to evaluate the efficiency or profitability of an investment.
SDK	Software Development Kit - a collection of tools and libraries to facilitate the development of applications.
SME	Small and Medium-Sized Enterprise.
TDM	Text and Data Mining
UI	User Interface - the point of interaction between a user and a digital system.

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