D2.8 – Analysis of Innovative Approaches to Market Monitoring – Draft 1

Work Package 2 – Uptake of Digital Agriculture & Forestry Technologies

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Executive Summary

*This deliverable constitutes the first of two deliverables related to Task 2.4, **"Analysis of Innovative Approaches to Market Monitoring."** Here, Deliverable D2.8, **"Analysis of Innovative Approaches to Market Monitoring – Draft 1,"** provides an initial analysis of innovative market monitoring approaches. The subsequent deliverable, D2.9, **"Analysis of Innovative Approaches to Market Monitoring – Final,"** will build upon this analysis with expanded insights and will be delivered in Month 28.*

In this analysis, we introduce a digital ecosystem approach to better understand the uptake of digital and data-driven innovations in agriculture and forestry. Traditional market-based models often focus solely on buyer-seller interactions and monetary value. In contrast, the digital ecosystem framework considers a broader network of actors, data flows, and relationships that shape how innovation spreads and creates value.

The analysis identifies five key actor types: digiproducers, collaborators, digiproduct users, data intermediaries, and peripheral data users. These actors interact across overlapping digiproduct and data ecosystems, and span both upstream (e.g., producers, policymakers) and downstream (e.g., farmers, foresters) segments. Innovations generate social data externalities, whereby data from one actor benefits others, further extending ecosystem impact.

To analyse how actors position themselves and interact, the study introduces the concept of ecosystem space, where strategic activities—termed ecosystem scoping—determine engagement, needs, collaboration, and role transitions. The PARATA principle (Potential, Relevant, and Targetable Actors) helps map these dynamics and inform engagement strategies.

Innovation diffusion is explored through cascading behaviour, social influence, and network effects. The Bass Diffusion Model is discussed to understand the roles of initial adopters and imitators in driving uptake. Adoption barriers and enablers are analysed using behavioural models that account for capability, opportunity, and motivation.

The study also considers innovative monitoring techniques, such as API-based data extraction and Large Language Models (LLMs), which enable real-time, scalable analysis. Combining top-down and bottom-up monitoring offers a comprehensive view of adoption dynamics. Finally, it is shown that forecasting adoption before usage data becomes available is made possible through intention surveys, analogical reasoning, and cross-ecosystem insights.

Together, these tools and concepts form a new framework for policymakers and stakeholders to monitor adaptive innovation in digital agri-forestry ecosystems.

1 Introduction

The growing availability of huge datasets and advancements in computer power have rapidly accelerated the relevance of digital and data-driven technologies in agriculture and forestry. These innovations are applied across diverse areas, including farm management information systems (Tummers et al., 2019), variable rate technologies (Pawase et al., 2023), robotics (Shamshiri et al., 2018), and controlled traffic farming (Chamen, 2015). Many of these technologies incorporate artificial intelligence (AI) to support predictive analytics, autonomous operation, and real-time decision-making (Kamilaris et al., 2017; Wolfert et al., 2017). An illustrative example is RootWave's AI-powered eWeeder, which removes invasive plants such as Giant Hogweed using electrical pulses rather than chemicals. This technology applies real-time waveform control to boil plant roots while preserving crops and surrounding soil structures (RootWave, 2023). Such systems demonstrate how digital solutions not only offer functional value but also represent environmentally conscious alternatives to traditional methods.

By design, digital solutions produce streams of data. These datastreams provide immediate operational benefits and long-term analytical insights, serving a dual purpose: solving user-level challenges while generating broader system-level knowledge. For instance, smart irrigation systems monitor and collect data on water usage, soil moisture, and crop responses. Analysts can use this data to assess real-world usage patterns, infer levels of adoption, and detect farmer-led modifications. Similarly, forestry machinery equipped with sensors logs data on terrain, harvesting frequency, and machine efficiency. These operational datastreams provide a bridge between the technical implementation of tools and the socio-economic context in which they are deployed (Kamilaris et al., 2017; Ganeshkumar et al., 2023).

Despite their promise, digital and data-driven innovations in agriculture and forestry lag in adoption compared to sectors like finance, healthcare, and manufacturing (Ganeshkumar et al., 2023; Oliveira & Silva, 2023). This underlines the importance for public policymakers and sector stakeholders to better understand how innovation diffuses across these domains and what enables—or inhibits—widespread adoption.

Traditionally, innovation diffusion studies have relied on user surveys to measure intentions or attitudes toward adopting new technologies. Additionally, econometric models have been used to analyse sales data to infer adoption rates and forecast trends. These methods remain important (Davis, 1989) but may be inadequate for capturing the full picture from massive data streams.

Digital and data-driven innovations inherently produce continuous datastreams not only post-market but also during earlier development stages. These datastreams may contain valuable information about potential adoption dynamics, such as user engagement during pilot phases or developer-farmer feedback loops before commercialization. However, the size and complexity of these data flows pose analytical challenges. Extracting meaningful insights requires advanced tools capable of filtering noise, identifying patterns, and contextualizing behavioural signals.

In this study, we explore how new approaches can improve our understanding of the drivers and barriers influencing the adoption of digital and data-driven technologies in agriculture and forestry. To anchor our analysis, we introduce the concept of the digital data ecosystem—a framework more encompassing than traditional market-oriented views. While markets focus primarily on transactions between buyers and sellers, a data ecosystem includes a broader range of actors who generate, use, or are affected by the accompanying datastreams.

To further operationalise our framework, we introduce the concept of ecosystem space, which captures how actors interact with and derive value from innovation across different stages of the product life cycle. These ecosystem spaces are not static; they evolve as technologies mature and adoption spreads. As this evolution unfolds, the nature and intensity of data use among stakeholders may also shift. By analysing ecosystem spaces specific to agriculture and forestry, we can identify key indicators of innovation diffusion that embed themselves in datastreams.

To extract and analyse such indicators from complex and large-scale data environments, we propose a hybrid approach. This combines traditional methods—such as econometric modelling and survey-based analysis—with modern tools like Application Programming Interfaces (APIs) and Large Language Models (LLMs). These digital tools enable the automated classification of data, detection of relational patterns, and real-time interpretation of user behaviour and sentiment across the ecosystem.

Our study develops this framework in a structured manner, beginning with the digital ecosystem, followed by sections on actors, social data externalities, and subsystems. We then elaborate the ecosystem space and its operationalization, before offering Illustrations from agri-forestry, examining change along the product life cycle, and exploring innovation diffusion, barriers and levers, monitoring techniques, and forecasting adoption and collaboration. We conclude with a synthesis of findings and their implications for ecosystem-based innovation policy and practice.

2 The Digital Ecosystem

The evolution of digital and data-driven innovations, along with their resultant data streams, can be examined through various lenses. For example, economists may approach innovations by analysing their impact on market structures; sociologists may examine how new data-driven technologies affect power dynamics; technologists may concentrate on the challenges related to system interoperability; jurists may address issues of regulatory compliance; etc. For policy makers who must navigate these diverse perspectives, there is a need for flexible terminology that can accommodate various viewpoints, enabling them to effectively harness collective expertise and research findings (see, among others, Ostrom, 2009; Saltelli et al., 2020).

In this study, we use the concept of a **digital ecosystem** as our point of departure. A digital ecosystem is a distributed, adaptive, and open socio-technical system characterised by self-organization, scalability, and sustainability (Briscoe & De Wilde, 2006; Nachira et al., 2007; Tan et al., 2020). It consists of diverse actors, such as users, developers, and intermediaries, who collaborate within a shared technical environment and depend on one another for value creation through data exchange, platform access, innovation, and infrastructure.

We argue that the term “digital ecosystem” is well-suited to describe the dynamics we observe. The actors involved engage in a wide range of interactions—such as data sharing, co-creation, and mutual learning—and often shift roles across contexts, for instance from data providers to users, or from collaborators to regulators, depending on the type of value being created. In contrast, alternative terms like “digital economy” may be too limited for capturing these fluid, multi-dimensional relationships. While a digital economy perspective is valuable in contexts where monetary exchange, pricing, and competition are central, it may overlook important non-monetized drivers and barriers that significantly influence impactful innovation.

In this respect, a case in point is the Solow Paradox: “You can see the computer age everywhere but in the productivity statistics” (Solow, 1987). This paradox illustrates that advancements in digital technologies may have limited reflection in traditional economic indicators, such as productivity or return on investment (ROI) (Brynjolfsson & Hitt, 1998; Brynjolfsson, Rock, & Syverson, 2017).

This is not necessarily due to a lack of effect, but rather because traditional indicators overlook intangible, relational dynamics, such as knowledge flows, data externalities, and network effects, that are critical for long-term new digital-product success.

We apply the concept of a digital ecosystem to agriculture and forestry, where technology and data integration are gaining momentum. Tools like milking robots, drone-based crop monitoring, and autonomous harvesters now serve as both machine and data sources, capturing real-time environmental and operational variables. These innovations optimise processes while generating continuous data streams that support efficiency and sustainability. For example, unmanned aerial vehicle (UAV)-based spectral data, combined with satellite and ground sensors, can assess crop vigor or detect disease at early stages, while light detection and ranging (LiDAR) in forestry informs sustainable logging and replanting (Primicerio et al., 2012; White et al., 2016).

The main message of this section for the 4Growth project is:

- Leverage the innovative concept of a digital ecosystem to study the uptake of digital and data-driven innovations, as it offers a more effective framework for capturing relevant indicators.

3 Actors in the Digital Ecosystem

The following typology outlines actors related to a digital or data-driven innovation within a digital ecosystem. They are visually represented in Figure 1.

Digiproducers. These actors develop new digiproducts, often by integrating data into physical innovation processes. For example, a precision agriculture startup developing AI-driven crop monitoring drones that use satellite and sensor data to optimise fertilizer use.
Collaborators. These include partners who contribute data, technology, or know-how along the product life cycle. Their collaboration supports innovation by providing essential inputs. For example, a weather data provider or soil sensor manufacturer supplying real-time data that feeds into a farm management platform.
Digiproduct users. These adopt and apply digiproducts in their operations. Their engagement is essential for validating utility, driving scale, and creating application-level value. For example, a vineyard manager using a digital disease prediction tool to plan fungicide application.
Data intermediaries. These collect, process, and distribute data between actors. They facilitate access, standardization, and trust in data exchange. These actors collect usage and performance data from technology users—often in exchange for insights, services, or platform access. For example, exchange platforms that aggregate farm data from various sources and make it accessible under standardised data-sharing agreements, for example, AgriGaia (Fraunhofer, 2023) or AgriDataSpace (AgriDataSpace, 2024).
Peripheral data users. These use data without being directly involved in the original digiproduct's creation or purchase (e.g., regulators, researchers, third-party service providers). They generate insights, ensure compliance, or create complementary value. For example, agricultural policy analysts using farm-level production data to shape subsidy programs, or NGOs assessing forest health using open-source satellite data.

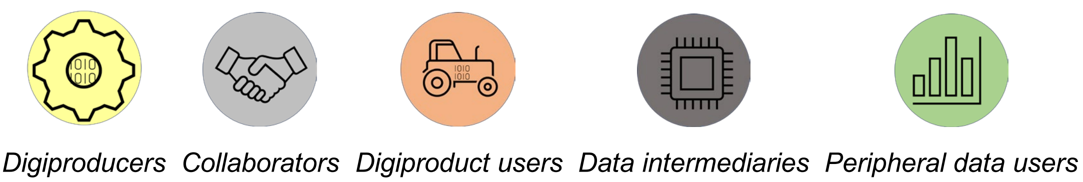

Figure 1 Actors in the data economy

The main message of this section for the 4Growth project is:

- Expand the scope of relevant actors beyond just digiproducers and digiproduct users by including collaborators, data intermediaries, and peripheral data users. This broader perspective, grounded in the innovative concept of a digital ecosystem, provides a more comprehensive understanding of the uptake of digital and data-driven innovations.

4 Social Data Externalities in the Digital Ecosystem

Social data externalities may play a pivotal role in the adoption of digiproduct innovations and the accompanying data generation.

Individual-level data often holds value beyond its original source. Because individuals in similar environments or with comparable behaviours tend to act alike, one person’s data can yield predictive insights about others—a phenomenon known as social data externalities (Bergemann et al., 2021). These occur when the data generated by one actor indirectly benefits others, often unintentionally.

In agriculture, for instance, when a farmer adopts a pest detection tool, the system may identify outbreak patterns that trigger alerts for neighbouring farms—even if they haven’t contributed data themselves (Bronson & Knezevic, 2016). Similarly, aggregated data from foresters using climate-adaptive planting tools can inform regional policy or ecosystem planning (Carbonell, 2016). Robotic weeders and soil sensors also generate externalities by supporting collective decisions in conservation, nutrient management, and risk mitigation (Eastwood et al., 2019).

These spillover effects enhance the overall utility of digiproduct innovations. For example, analysing technology adoption patterns—such as precision irrigation or automated milking—helps suppliers refine pricing, timing, and targeting strategies. Equipment-as-a-service platforms can further optimise their business models using initial adopter data to adjust subscription tiers or forecast regional demand (Rotz et al., 2019). A visually representation is presented in Figure 2.

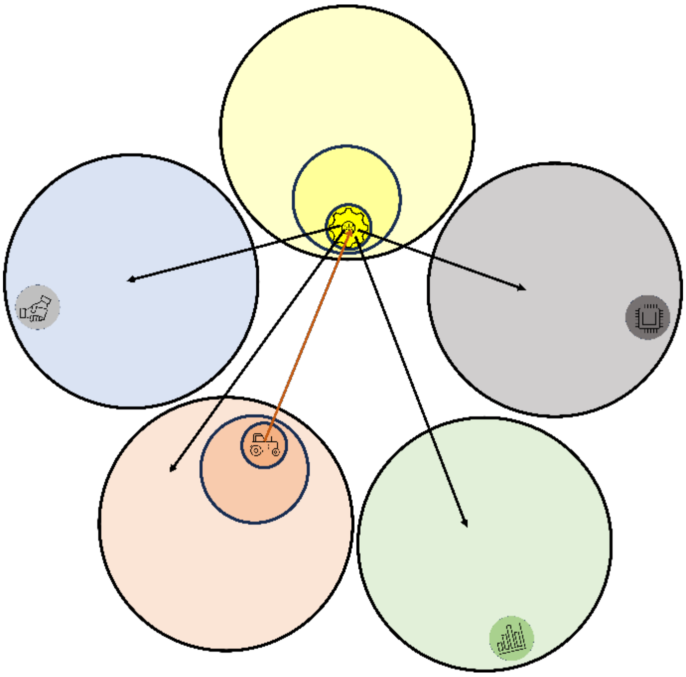

Figure 2. Social data externalities

The main message of this section for the 4Growth project is:

- The phenomenon of social data externalities shows why the uptake of digital and data-driven innovations affects more actors than just the direct, physical users of the innovation. It is therefore fair to state that a digital and data-driven solution has a broader impact on the agriculture and forestry sectors than simply meeting the needs of its immediate users.

5 Subsystems of the Digital Ecosystem

In this study, we consider two types of subsystems within the digital ecosystem: digiproduct and data ecosystems, and upstream and downstream ecosystems.

5.1 The digiproduct and data ecosystems

Within the digital ecosystem, we distinguish between the digiproduct ecosystem and the data ecosystem. These subsystems may overlap, as actors can participate in multiple subsystems simultaneously or shift between them over time. Such shifts often depend on the specific context or perspective—whether economic, social, legal, or otherwise. For instance, an actor may perform as a data intermediary in one setting while functioning as a digiproduct innovator in another. We believe that understanding these dynamic roles and overlaps is crucial for analyzing how value is created, exchanged, and regulated within complex, multi-actor digital environments.

A **digiproduct ecosystem** revolves around a digitalised product or service —a physical or analogue offering enhanced with digital technologies to enable data collection, interaction, and value creation through connectivity, intelligence, or integration (Porter & Heppelmann, 2014; Raff et al., 2020; Tan et al., 2020). Digiproduct users decide which technologies to adopt, while developers and manufacturers (innovating producers) supply innovations that aim to fully align with user-specific needs. Product success depends on criteria, such as usability, perceived benefits, and low integration costs.

On the other hand, a **data ecosystem** is a dynamic network of actors who generate and use data to create value (Oliveira & Lóscio, 2018; Heinz et al., 2022; Lnenicka et al., 2024). Commonly, value arises not from raw data, but from its combined use to inform decisions, customise services, and drive innovation. Data intermediaries are central, enabling data to be shared for benchmarking or decision-making, or sold to innovators for product development, marketing, or personalization.

5.2 Upstream and downstream ecosystems

The dynamics of ecosystems are shaped by upstream and downstream actors (Molner et al., 2019). Successful innovation goes beyond technical skill, requiring engagement with upstream partners—such as universities, research institutes, and patent offices—to align with emerging technologies and standards (Adner, 2006). Simultaneously, innovators must understand downstream user needs to ensure relevance and adoption (Teece, 2018). Neglecting upstream trends like data-driven advances may result in missed opportunities, while ignoring user demands can lead to market failure. Effective innovation thus depends on finetuning between technological frontiers and real-world applications.

Upstream ecosystems include actors that provide foundational technologies, resources, and expertise. In digiproduct ecosystems, these may be universities, manufacturers, test labs, and component suppliers (e.g., sensors, software, valves), who ensure technical viability, interoperability, and scalability. In data ecosystems, upstream actors include software developers, data scientists, analytics providers, and cloud infrastructure firms. These stakeholders create the platforms, standards, and algorithms that underpin secure, reliable, and interoperable data sharing (Lindgren et al., 2021). Their collaborative input is essential for shaping innovations that are future-proof and integrated into broader system architectures.

Downstream ecosystems consist of users and decision-makers who evaluate and apply innovations. In digiproduct ecosystems, this includes farmers, foresters, agribusinesses, and public agencies whose choices determine market success. Their feedback informs upstream design and adaptation. In data ecosystems, downstream users engage with tools such as dashboards, decision-support systems, and farm management apps. Their trust in the quality, usability, and contextual relevance of data is critical for effective uptake (Carboni et al., 2021). Ultimately, downstream engagement shapes both the adoption trajectory and the realised value of innovation.

An overview of these ecosystems is provided in Figure 3.

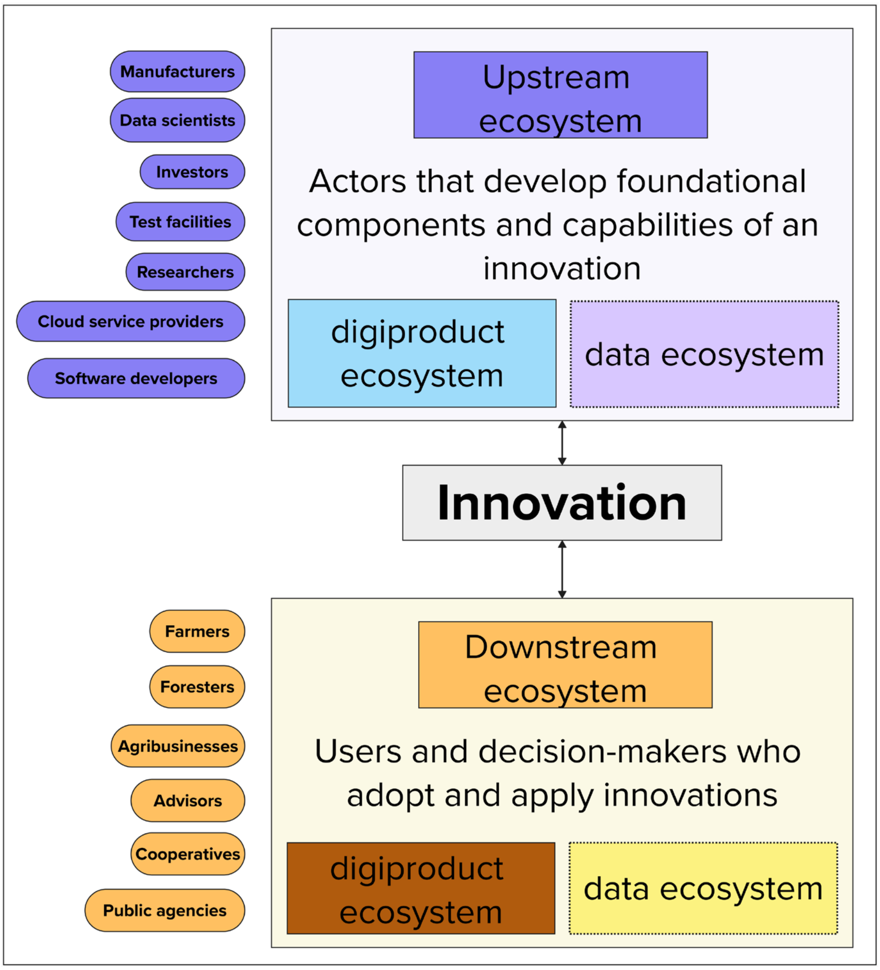

Figure 3. The subsystems of the digital economy

The main messages of this section for the 4Growth project are:

- Digital ecosystems are composed of interconnected and overlapping digiproduct and data ecosystems. Understanding these subsystems helps explain how value is created and exchanged through both digital products and data flows, with actors shifting roles across subsystems.
- Innovation success depends on the interaction between upstream and downstream ecosystems. Upstream actors (e.g., universities, developers, infrastructure providers) contribute foundational technologies and standards, while downstream actors (e.g., farmers, foresters) determine adoption through their needs and feedback.

6 The Ecosystem Space

In this study, we introduce the concept of **ecosystem space** to describe the specific configuration of linkages through which the innovation potential of digital and data-driven technologies is realised. These linkages can include formal partnerships, informal knowledge flows, regulatory connections, and market relationships that together shape how actors interact with one another and with technological developments. Closely related to this is the concept of **ecosystem scoping**, which refers to the strategic activities undertaken by actors to explore, shape, and position themselves within these configurations. These activities include identifying relevant collaborators, anticipating competitive dynamics, adapting to regulatory frameworks, and influencing standards and norms (Jacobides et al., 2018; Adner, 2006).

Our approach builds on the work of Molner et al. (2019), who proposed the notions of market space and market scoping to analyse how emerging technologies develop within market contexts. In their framework, market space reflects the institutional and structural environment where economic transactions take place, while market scoping describes how actors seek to define their roles and opportunities within it. We adopt this foundation but extend the scope to include non-monetary forms of value—such as data access, reputational influence, and knowledge exchange—that are increasingly relevant in digital ecosystems. As such, market space is reframed as ecosystem space, and market scoping becomes ecosystem scoping

Ecosystem scoping, by definition, is actor-dependent. That is, the structure and boundaries of an actor’s ecosystem space are determined from their particular perspective, which is shaped by their goals, resources, and institutional constraints. For instance, sector regulators operating under European Union policy frameworks may engage in ecosystem scoping by identifying targetable digiproducers—actors that develop digital or data-driven solutions aligned with strategic policy goals such as environmental sustainability or data sovereignty. These regulators may use mapping tools, industry networks, or public datasets to determine which producers warrant investment, support, or compliance monitoring (Jacobides et al., 2018; Klerkx & Begemann, 2020).

From the perspective of digiproducers themselves, however, ecosystem scoping may unfold differently. Producers are unlikely to conceptualise their peers as "targetable" but instead categorise them as competitors or collaborators, depending on the nature of the innovation and their strategic positioning. The act of identifying others in the ecosystem is thus filtered through a lens of competitive intelligence, risk management, and innovation opportunity.

The main messages of this section for the 4Growth project are:

- Leverage the innovative concept of an ecosystem space to understand the networked environment in which digital and data-driven innovation unfolds, because it is therefore essential for identifying innovation potential within an ecosystem.
- Use the innovative concept of ecosystem scoping to study the strategic activities of actors when they define their position and relationships within their ecosystem space. Unlike traditional market scoping, these activities may also incorporate non-monetary forms of value like data access and knowledge bases.
- Be aware that ecosystem scoping is highly actor-specific, meaning that different actors perceive and shape their ecosystem in different ways. This calls for policy tools that support diverse scoping strategies across different actor perspectives.

7 Operationalization of Ecosystem Scoping

The actor-centric variation also influences how ecosystem scoping is operationalised. Regulators may rely on databases, compliance frameworks, and standardised indicators, while producers may use informal networks, market intelligence, or proprietary tools. Furthermore, actors' scoping strategies evolve as products move through different stages of the innovation lifecycle—from conceptualization and prototyping to market launch and diffusion. At each stage, new actors emerge, and the configuration of the ecosystem space shifts accordingly. This dynamism underscores the need to monitor not only adoption rates or market penetration, but also changes in ecosystem configuration over time (Gómez-Limón et al., 2022).

To identify promising configurations, actors may use a sizing principle. A widely applied framework in monetised settings is the TAM–SAM–SOM model, which segments opportunity from broad potential to narrow feasibility (McKinsey & Company, 2014; Cooper & Vlaskovits, 2010). In this classification, the Total Addressable Market (TAM) represents the maximum revenue opportunity; the Serviceable Available Market (SAM) reflects what is realistically addressable; and the Serviceable Obtainable Market (SOM) defines what can be realistically captured given constraints.

We adopt this scaling logic—but shift the focus from monetised segments to engagement segments. Applied to digital ecosystems, we distinguish three levels: Potential Actors (PA), Relevant Actors (RA), and Targetable Actors (TA). This results in, what we propose to call, the PA–RA–TA (PARATA) principle. To our knowledge, this is the first application of such a sizing principle to ecosystem engagement. In Figure 4, we graphically depict the PARATA principle.

Targetable Actors can be further categorised into innovating and imitating actors, based on their mode of engagement in digital or data-driven innovation. Understanding the distinction between innovating and imitating actors is crucial for analysing the long-term dynamics of the adoption process (Bass, 1969).

Innovating actors become engaged on their own initiative, without being influenced by peer behaviour. They may enhance digiproducts or data infrastructure by sharing expertise, offering feedback, or co-developing features. For example, a forestry cooperative may refine a biodiversity tracking app by contributing field data and collaborating with developers to improve functionality (Ostrom, 1996; von Hippel, 2005).

Imitating actors adopt innovations after observing peer behaviour. Though not drivers of innovation, they play a vital role in scaling and diffusion within the ecosystem. For instance, smallholder farmers may adopt smart irrigation systems after witnessing positive outcomes on neighbouring farms (Rogers, 2003; Ghadim et al., 2005).

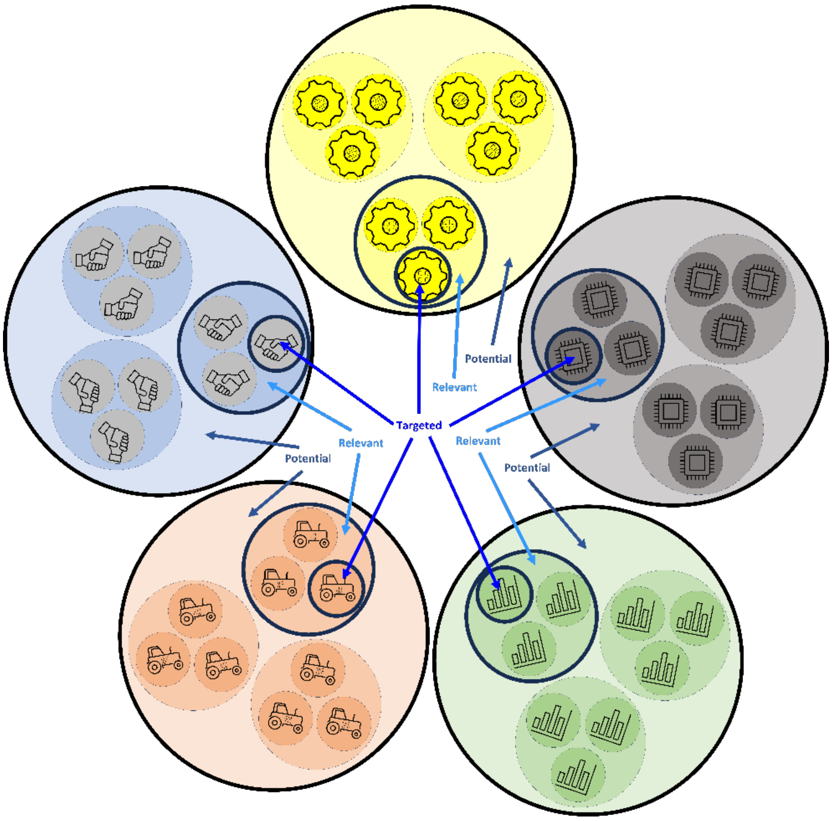

Figure 4. The PARATA hierarchy

The main messages of this section for the 4Growth project are:

- Apply the innovative PARATA principle to distinguish between Potential Actors (PA), Relevant Actors (RA), and Targetable Actors (TA). This framework helps identify who could engage, who should engage, and who can realistically be influenced or supported by the focal actor. The PARATA principle is inspired by the TAM–SAM–SOM model but adapted to ecosystem engagement rather than market sizing.
- Distinguish between innovating and imitating actors, as they play different dynamic roles in the uptake of innovation within an ecosystem. Innovating actors often proactively initiate and co-develop solutions, whereas imitating actors adopt innovations after observing their success.

8 Illustrations of Digital Ecosystem Spaces in Agri-Forestry

This section presents illustrations of digital ecosystem spaces, including upstream and downstream linkages—within and between digiproduct and data ecosystems—through which innovation potential is realised in agriculture and forestry (see figure 5).

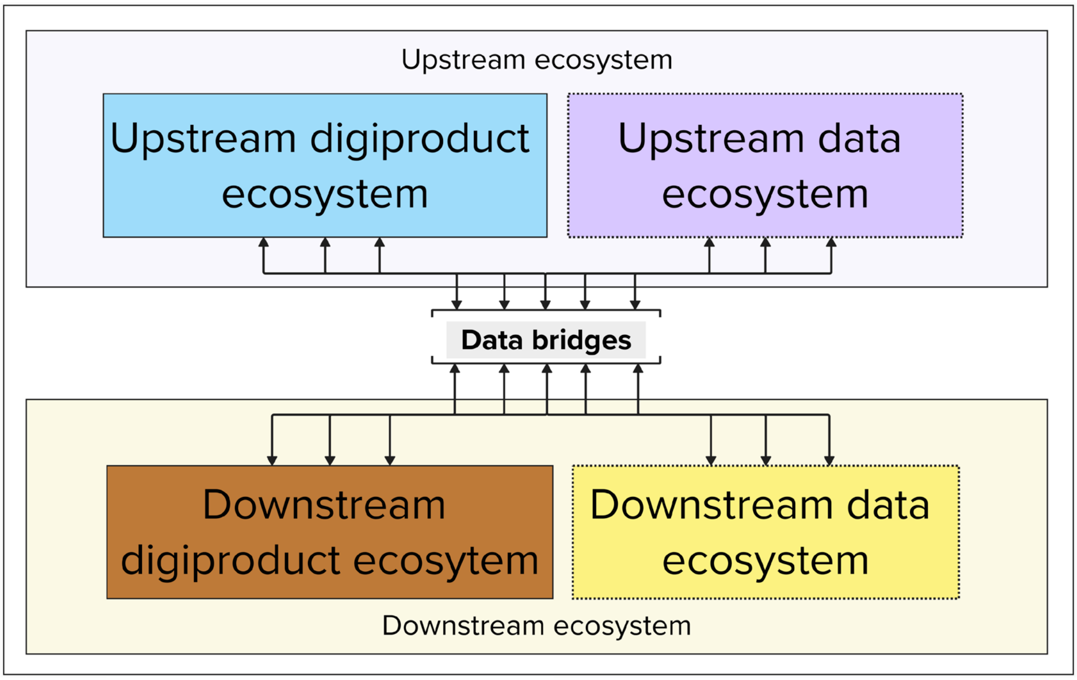

Figure 5. Data linkages across the different subsystems of the digital ecoystem

8.1 Bridging upstream and downstream in the digiproduct ecosystem

Data flows generated by digital technologies may connect upstream and downstream actors within the digiproduct ecosystem. Take, for example, an automated milking robot: while designed to streamline farm operations, it also collects data on animal health, milk yield, and equipment performance. This information is relayed to upstream actors, such as digiproduct developers and test labs, who can use it to refine the milking robot and its hardware based on real-world usage (Eastwood et al., 2016). Such feedback loops enable continuous innovation driven by end-user environments. Similar dynamics apply to robotic harvesters (e.g., the White Shark series) and unmanned aerial vehicles (UAVs) used for precision spraying. These tools collect valuable operational data that can lead to design improvements, such as enhanced sensor calibration for sloped terrain or more accurate canopy mapping in orchards (Zhang & Kovacs, 2012; Pedersen et al., 2018). These examples illustrate how field data informs iterative innovation across the ecosystem. A visual representation is presented in Figure 6 and 7.

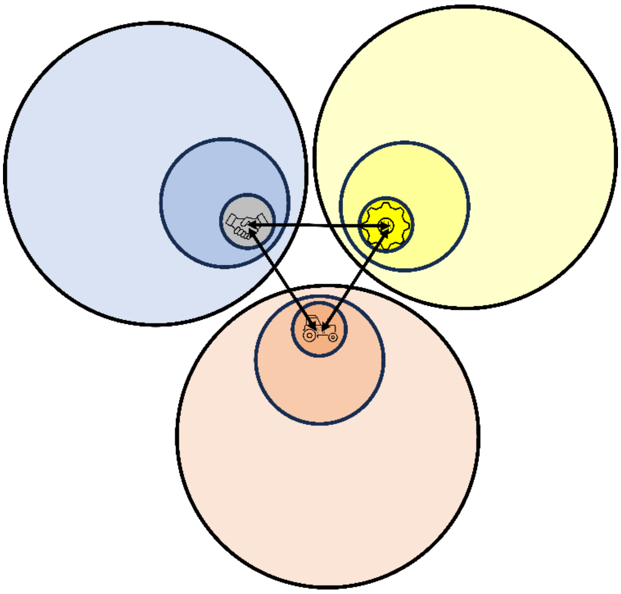

Figure 6. Bridging Upstream and Downstream in the Digiproduct Ecosystem

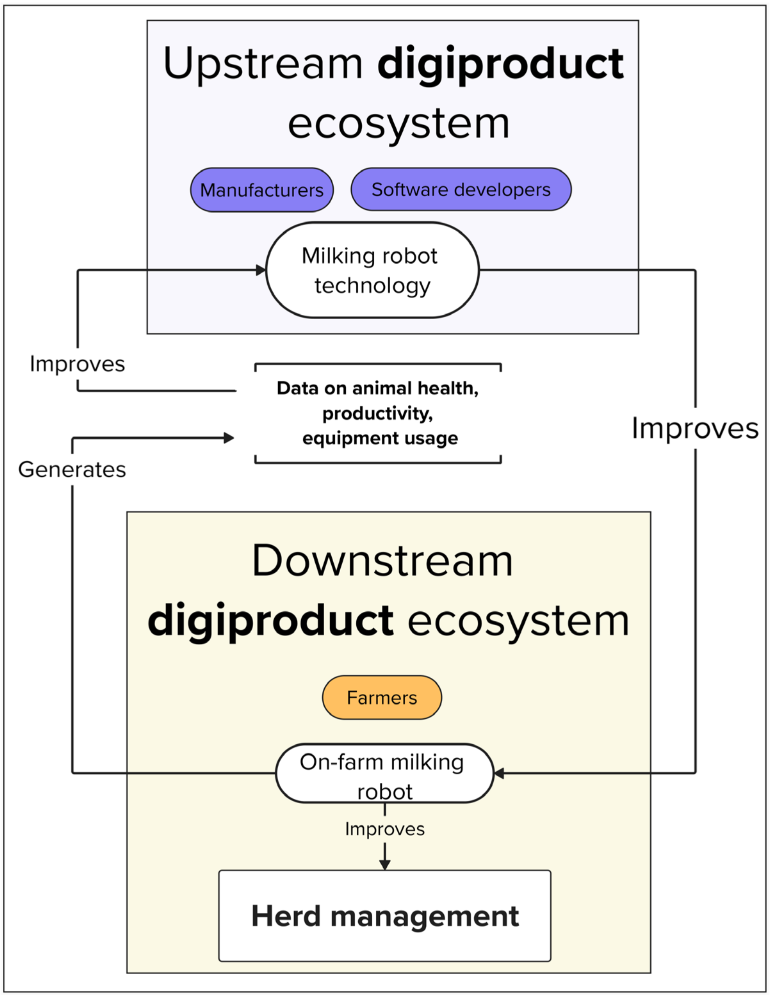

Figure 7. Data bridges: milking robot

8.2 Bridging upstream and downstream in the data ecosystem

In the data ecosystem, upstream actors—including cloud infrastructure providers, analytics developers, and research institutions—create the essential frameworks and tools for storing, processing, and sharing agricultural and forestry data. For example, startups developing machine learning models for crop disease detection collaborate with infrastructure providers for data storage, model training, and computational capacity (Kamilaris & Prenafeta-Boldú, 2018).

Downstream, actors such as farmers, agronomists, cooperatives, regulators, and researchers apply these insights in practical decision-making. Farm Management Information Systems (FMIS) exemplify this connection, integrating data from sensors, UAVs, and agricultural robots to generate actionable intelligence through dashboards and analytics tools (Liakos et al., 2018). These platforms also return aggregated and anonymised trends to upstream developers, enabling iterative improvements. Forestry decision support systems (DSS), like EFISCEN (European Forest Information Scenario model) and C.A.F.E. (Carbon Accounting and Forestry Evaluation), further demonstrate how field-level data can inform regional and continental planning, emphasizing the need for participatory data sharing and cross-scalar integration (Arets et al., 2011; Cimini et al., 2013).

Here, the data bridge is as follows: it translates field-level inputs into decisions for downstream users while simultaneously informing upstream development about performance, user needs, and context-specific challenges. A visual representation is presented in Figure 8 and 9.

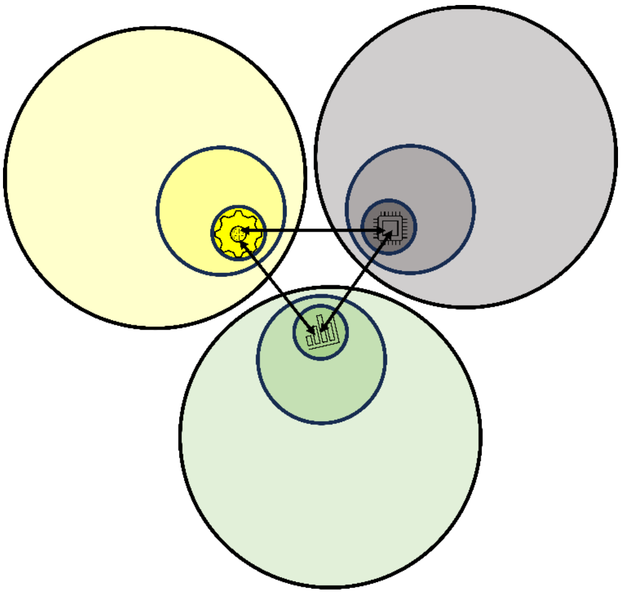

Figure 8. Bridging Upstream and Downstream in the Data Ecosystem

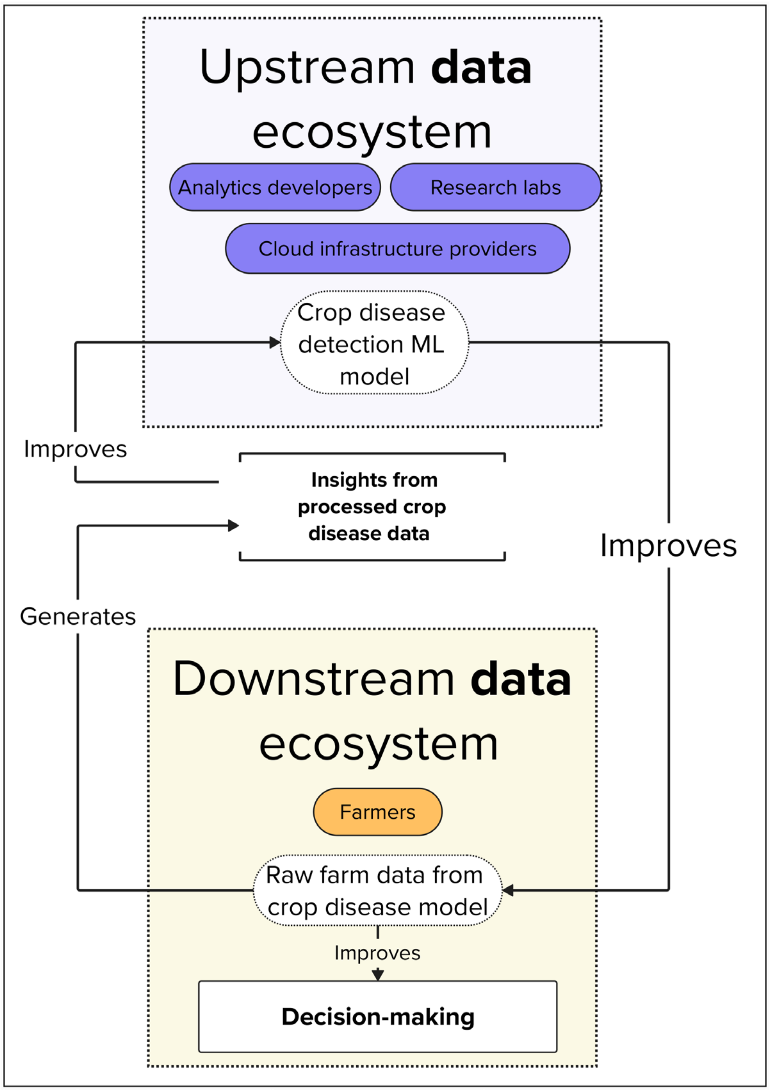

Figure 9. Data bridges: crop disease detection model

8.3 Bridging upstream in digiproduct and data ecosystems

Innovative digital and data-driven production requires close coordination between digiproduct developers and data system providers. For example, precision sprayer developers must collaborate with data engineers to ensure that sensor outputs are accurately captured, transmitted, and analysed in real time (Liakos et al., 2018). A more complex case is the SpectroFood platform, which integrates imaging spectrometry for post-harvest quality assessment. This required alignment among camera manufacturers, spectral calibration specialists, and cloud-based analytics providers to deliver reliable, real-time insights (Tsouvaltzis et al., 2021). In such systems, data functions as a critical bridge—linking physical devices with the digital infrastructure that enables performance monitoring and decision support. Shared datasets allow upstream actors, including both hardware and software developers, to coordinate development, promote interoperability, and create integrated solutions tailored to end-user environments (Walter et al., 2017). A visual representation is presented in Figure 10 and 11.

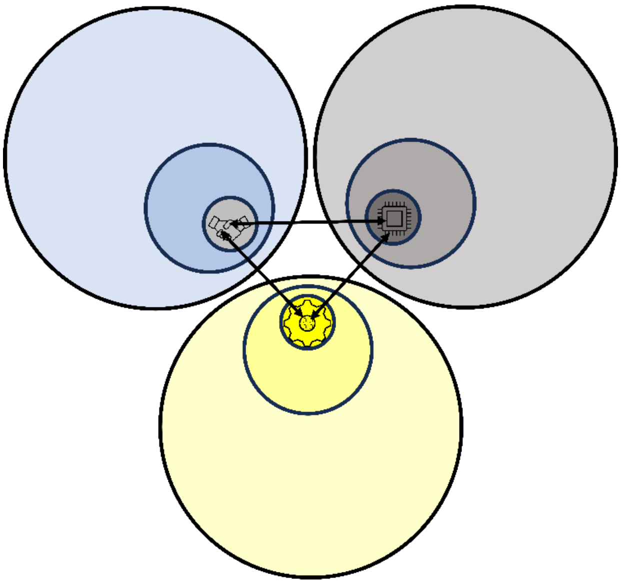

Figure 10. Bridging Upstream in Digiroduct and Data Ecosystems

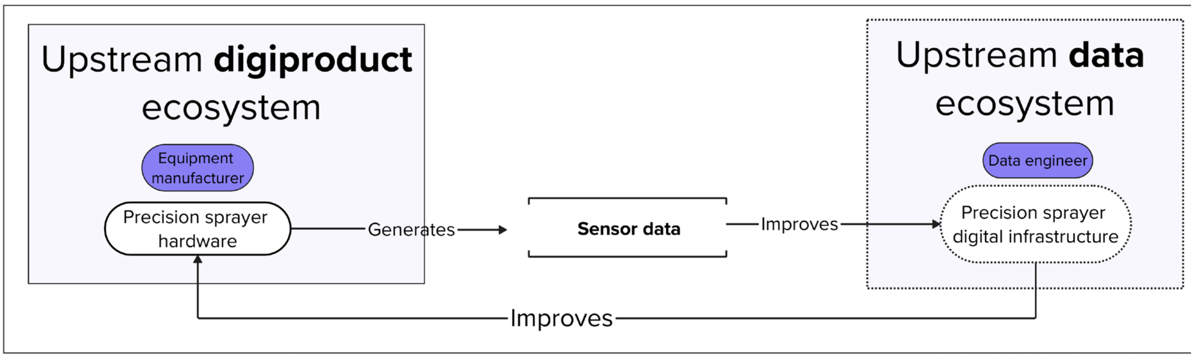

Figure 11. Data bridges: Precision sprayer development

8.4 Bridging downstream in digiproduct and data ecosystems

Farmers, technology developers, regulators, and researchers may be interconnected through mutual interests and policy agendas. Farmers, as digiproduct users, generate real-time data using precision agriculture tools such as soil sensors, drones, and farm management platforms. This data not only supports immediate decision-making but also feeds back to developers, who refine digital tools based on real-world performance (Liakos et al., 2018). Simultaneously, regulators increasingly rely on these data streams—often aggregated and anonymised—to inform sustainability policies and compliance mechanisms. For instance, on-farm data about pesticide use, carbon emissions, or nutrient management is used to support evidence-based policy design (OECD, 2019).

This interaction is not unidirectional. Regulatory frameworks influence which practices are adopted on the ground, while innovations at the farm level can challenge regulatory assumptions or highlight the need for updates. Cooperatives may act as intermediaries, providing collective datasets that help shape regional policies, such as soil health monitoring. These policies, in turn, stimulate the development of new sensing technologies or data platforms. This creates a continuous feedback loop where policy, innovation, and practice co-evolve—driving adaptive governance in agri-food systems (Klerkx & Begemann, 2020). For example, adoption of cloud-based farm dashboards in Galicia and Flanders spurred improvements in visualization tools for winegrowers and livestock farmers (Lajoie-O'Malley et al., 2020). A visually representation is presented in Figure 12 and 13.

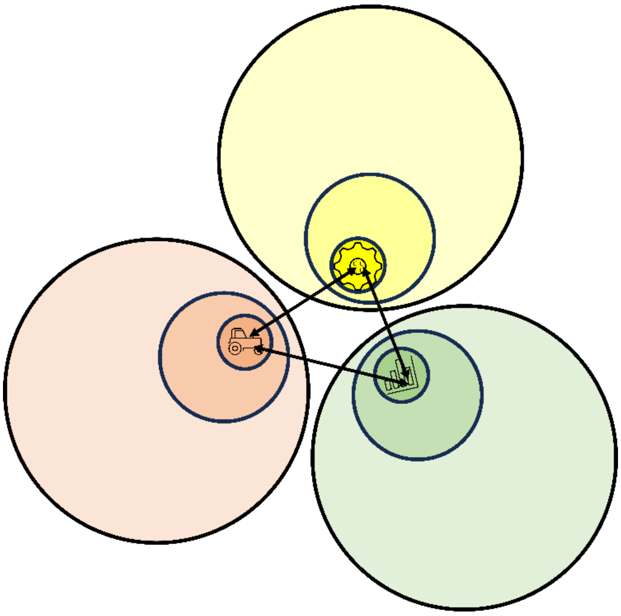

Figure 12. Bridging Downstream in the Product and Data Ecosystems

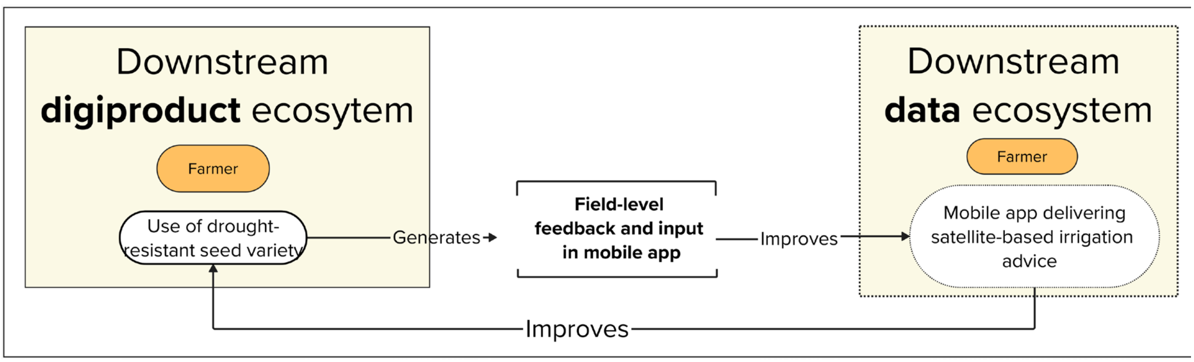

Figure 13. Data bridges: Irrigation advice mobile app and drought-resistant seed variety

9 Along the Product Life Cycle

As innovations in digital ecosystems evolve, ecosystem scoping has to account for shifting actor roles along this evolution. Indeed, actors engage in diverse activities—such as data sharing, co-creation, and feedback loops—and may switch roles depending on context, moving from user to provider or from collaborator to regulator (Jacobides et al., 2018). Understanding the stage of an innovation's life cycle is therefore crucial, as it influences data user engagement, adoption dynamics, and the type of ecosystem support needed (Moore, 1996).

In early stages of development, upstream actors may play a central role and feedback from pilot users may be essential to refining technologies. For example, early-stage testing of AI for strawberry ripeness involved close collaboration between data scientists and farmers to calibrate visual thresholds and harvesting logic (Kamilaris & Prenafeta-Boldú, 2018).

In contrast, in mature phases, cross-network feedback loops, e.g., from downstream product use to upstream data refinement, may reveal new use cases and latent demand. Such information commonly guides further integration, stimulates innovation, and signals where policy or interoperability support is needed (Klerkx & Begemann, 2020). So, ecosystem scoping is recommended to evolve along the PLC.

The **Product Life Cycle** (PLC) describes the progression of a product from initial development to market decline. It typically comprises two management perspectives: product-life-cycle engineering, which covers stages from concept to market readiness, and product-life-cycle marketing, which focuses on stages from market entry to eventual phase-out. Understanding the PLC is vital for guiding strategic decisions, optimizing investments, and aligning innovation efforts across the product's lifespan (Kotler & Keller, 2016).

When dealing with technological innovations (to which most of the digital and data-driven innovations belong), the PLC can be complemented by Technology Readiness Levels (TRLs)—a nine-level scale used to assess technological maturity, from basic research (TRL 1) to full market deployment (TRL 9). Originally developed by NASA and now widely applied across sectors—including agriculture, forestry, and food systems—TRLs help manage innovation pipelines, reduce risk, and align development efforts with commercial timelines (Mankins, 1995; OECD, 2017).

As technologies advance through the PLC, ecosystem scoping strategies must also evolve. In early phases (TRL 1–3), scoping is commonly exploratory: partners, markets, and use cases are often undefined. As innovation matures, scoping becomes more targeted, focusing on identifying relevant actors, building relationships, and aligning infrastructure. Molner et al. (2019) emphasis

that successful innovation requires dual attention to both market demand and supply-side collaboration.

Stages of the Product Life Cycle and Associated TRLs

Conception Phase (TRL 1–3): In this stage, basic research occurs. TRL 1 involves identifying fundamental principles; TRL 2 includes concept formulation; and TRL 3 tests initial feasibility, such as early lab work on sensing technologies for crop monitoring.

Design Phase (TRL 4–6): The technology progresses into lab validation (TRL 4), testing in relevant environments (TRL 5), and demonstration in simulated field conditions (TRL 6). For example, prototypes of AI-based harvesters may be field-tested in controlled orchard plots (Kamilaris & Prenafeta-Boldú, 2018).

Product Realization (TRL 7): Here, the system is built and demonstrated in operational settings. Manufacturers begin scaling production and establishing value chains.

Market Entry (TRL 8): The product is certified and launched commercially. Focus shifts to user adoption, pricing, distribution, and performance feedback.

Market Growth (TRL 9): The technology sees wider adoption and integration into operational routines. Data from users feeds back into iterative updates and support services.

Market Maturity (TRL 9): Market saturation sets in, competition intensifies, and strategies shift to differentiation, cost efficiency, and retention.

Market Saturation/Decline (TRL 9): Demand slows due to competing innovations or shifting needs. Companies may phase out the product or invest in complementary upgrades to extend lifecycle value.

The main message of this section for the 4Growth project is:

- Recognise that actors may transition between roles—such as from peripheral data user to collaborator—depending on their own innovation phase and that of the other ecosystem actors they interact with.

10 How Innovation spreads in an Ecosystem

10.1 Cascading behaviour

Individual decisions in ecosystems can lead to cascading behaviour, where people sequentially update their choices based on both personal beliefs and the observed actions of others. Easley and Kleinberg (2010, p. 878) describe this dynamic as a process in which a default behaviour is altered by a small group of initial adopters who switch to a new behaviour they perceive as superior. Their decision can influence connected individuals, who may in turn adopt the new behaviour, potentially triggering a broader cascade. Whether this cascade continues or halts depends on the ecosystem structure, the positioning of the initial adopters, and the behavioural thresholds of others in the ecosystem.

Cascades are more likely in tightly connected or clustered ecosystems, especially when social influence outweighs individual information (Centola, 2010). Empirical studies in areas such as online product adoption, social media trends, and sustainable practices demonstrate how diffusion is shaped by both peer influence and ecosystem architecture (Aral & Walker, 2012; Centola et al., 2018). Such insights help explain how new behaviours, ideas, or technologies gain momentum (or stall) within social systems.

Two underlying dynamics that help to explain the influence on connected actors in a digiproduct ecosystem include social effects and network effects.

10.2 Social effects

In the relevant literature, social effects are also referred to as internal effects. Easley and Kleinberg (2010, p. 872) point out that our understanding of behavioural cascades builds on foundational work in the sociology of innovation diffusion. A seminal study by Ryan and Gross (1943) examined how farmers in Iowa adopted hybrid seed corn. While initial awareness often came from salesmen, the decision to adopt was primarily influenced by observing neighbors' successful experiences. This person-to-person transmission of behavioural cues remains central to contemporary diffusion research. More recent studies confirm that social learning, peer influence, and perceived social proof strongly shape adoption decisions, from agricultural technologies to digital tools (Centola, 2010; Valente, 2012; Iyengar, Van den Bulte, & Valente, 2011).

10.3 Network effects

Network effects arise when the value of a product or service increases with the number of users. For example, in a digital equipment-sharing platform, each additional user not only broadens the pool of tools but also adds usage data that helps optimise resource allocation, hence, boosting value for all participants (Koutroumpis et al., 2020). Similarly, forestry decision-support systems become more accurate as more users contribute real-time data on soil and weather, improving sustainability outcomes over time (Ingram & Maye, 2020). These dynamics create positive feedback loops, where growing participation enhances utility, and consequently, attracting further adoption. This self-reinforcing pattern, rooted in the foundational work of Farrell & Saloner (1985, 1986) and Katz & Shapiro (1985, 1986), is central to understanding platform success and market dominance. Cooperative agri-platforms that integrate data pooling with collaborative services generate compounding benefits—improving functionality as both users and data grow. This synergy accelerates innovation diffusion and enhances decision-making across agricultural ecosystems (Bronson & Knezevic, 2016; Klerkx et al., 2019; Eastwood et al., 2021).

In real-world agri-forestry ecosystems, we observe that behavioural cascades often start with trusted intermediaries such as farm advisors, cooperatives, or Living Labs. These actors play a critical role in reducing uncertainty around new digiproducts by facilitating demonstration events where initial adopters showcase the practical value of innovations such as, for example, electric weeders (eWeeders), farm management information systems (FMIS), and drone-based crop monitoring. These peer-led demonstrations create observable success stories that may influence others' perceptions and lower the threshold for adoption (Labarthe & Laurent, 2013; Schut et al., 2019). Living Labs may function as collaborative platforms where farmers, researchers, and ag-tech developers co-create and validate innovations under real-world conditions (Ballon et al., 2018). Empirical studies have shown that such embedded social learning environments increase trust, may accelerate diffusion, and help innovations scale beyond initial adopters (Klerkx et al., 2019; Bacco et al., 2022).

10.4 Bass diffusion model

One of the most widely used tools for modeling the cascading behaviour of adoption is the Bass Diffusion Model (Bass, 1969; Grasman&Kornelis, 2019), which distinguishes between three key elements:

- Initial adopters: Those who embrace innovations without requiring validation from others. For instance, a tech-savvy farmer who installs a new soil sensor before it is widely known.
- Imitating adopters: Those who adopt based on social influence, typically after observing successful use cases.
- Size of the ecosystem: The total number of targetable actors. For example, all farmers in a region who could benefit from a given sensor.

Bass diffusion models have also been applied in data ecosystems. Katona et al. (2011) model diffusion within online networks, showing how local structure, adopter characteristics, and peer influence—via the degree and clustering effects—shape adoption. Similar dynamics appear in agri-forestry cooperatives and Living Labs, where peer trust accelerates innovation spread (Eastwood et al., 2021). Kreng and Tsai (2003) integrate Bass models with activity-based costing, illustrating how knowledge diffusion impacts enterprise value through past performance, knowledge investments, and knowledge flows. Recent studies emphasise how network structure and social learning jointly drive diffusion in agricultural and digital contexts (Gómez-Limón et al., 2022).

10.5 Visualization of innovation spread in an ecosystem

To illustrate the cascading behaviour during the diffusion of an innovation within an ecosystem, we present a visualization of a hypothetical scenario. Figure 14 shows an innovation spreading over time in an ecosystem graphically represented as a network. In this network, nodes represent actors, and edges denote their connections. We assume that all 128 actors in the ecosystem are targetable and will eventually adopt the innovation.

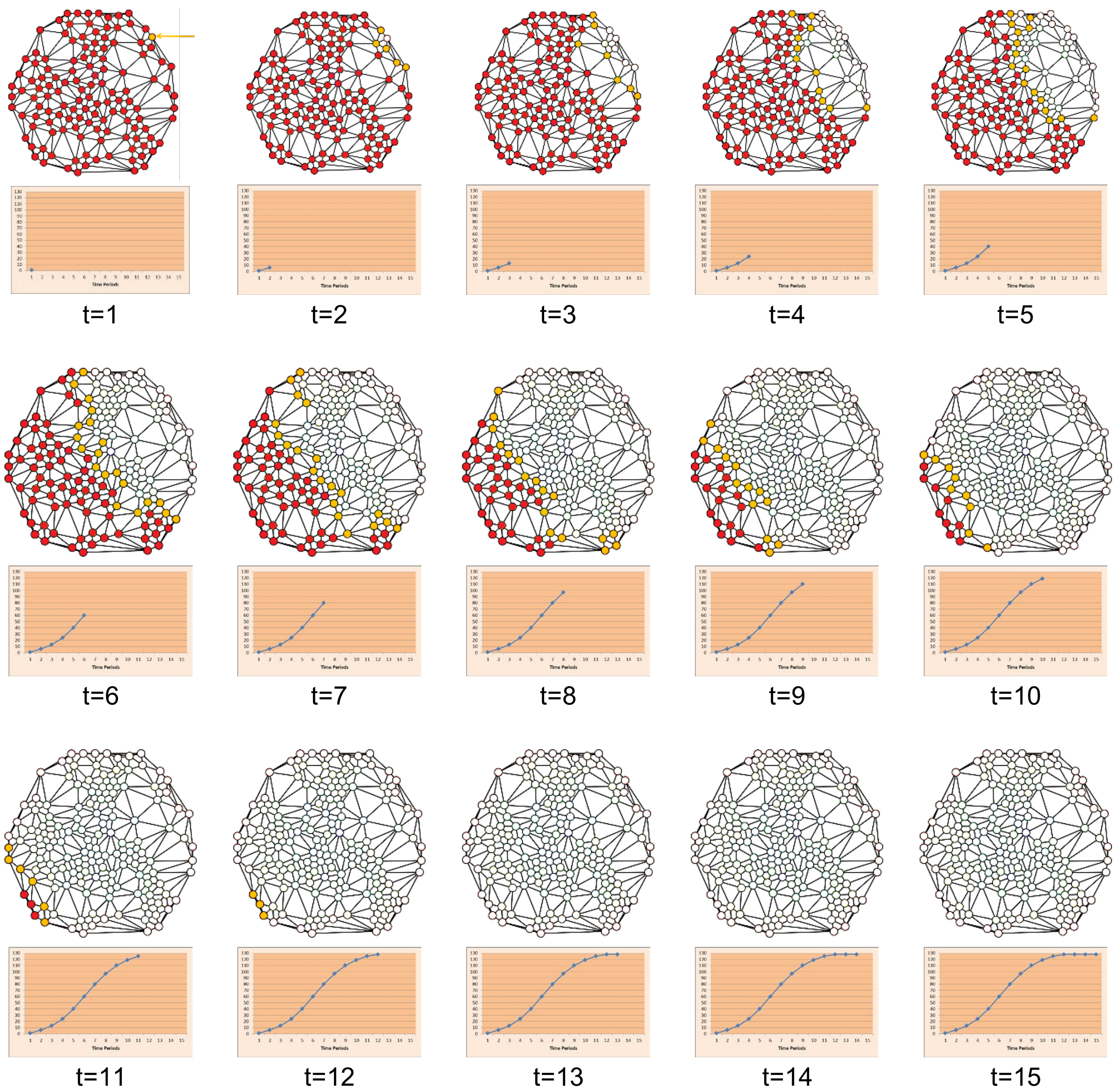

Figure 14. Diffusion of Innovation with one initial adopter and 127 imitating adopters

Our hypothetical process begins with one initial adopter, while the remaining 127 actors are imitating adopters. From left to right and top to bottom, the figure visualises the step-by-step diffusion process. At time step t = 1, the initial adopter, marked by a gold arrow in the figure, adopts the innovation. The graph below the network image tracks the cumulative number of adopters. At t = 1, only the initial adopter is counted. This adopter is directly connected to five other actors. Influenced by this connection, these five actors adopt the innovation at t = 2. They are represented as gold-colored nodes. The total number of adopters then increases to six.

This imitation process continues in subsequent time steps. As more actors adopt the innovation based on their connections to prior adopters, the diffusion cascades throughout the network. By t = 15, all targetable actors have adopted the innovation. The accompanying graph illustrates how this cascading behaviour results in a sigmoidal (S-shaped) adoption curve, a common pattern in innovation diffusion and product life cycles.

The main messages of this section for the 4Growth project are:

- Recognise that innovation diffusion in ecosystems is often driven by cascading behaviour, where individual adoption decisions influence others across the network. This process is shaped by social effects such as peer influence, social learning, and perceived success, which collectively lower the barriers to adoption.
- Understand that network effects significantly amplify the value of innovations as more actors participate, creating self-reinforcing loops of adoption and improvement. Cooperative agri-platforms are particularly well-positioned to harness these effects by combining shared data.
- Apply models such as the Bass Diffusion Model to analyze the roles of initial adopters, imitators, and the size of the targetable ecosystem. These models offer insights into how adoption spreads.

11 Understanding Barriers and Leverages in an Ecosystem

Since the 1960s, researchers have developed models to explain why individuals and organizations adopt or reject innovations. A foundational work is Rogers' Diffusion of Innovations theory (1962), which identifies five key attributes influencing adoption: relative advantage (perceived superiority over existing solutions), compatibility (fit with existing values and practices), complexity (ease of understanding and use), trialability (ability to experiment before full adoption), and observability (visibility of benefits). This model has been integrated theories of individual behavioural change, notably those by Ajzen and Fishbein (1980), who emphasise attitudes, subjective norms, and perceived behavioural control as key factors to predict changing behaviour.

Over time, sector-specific adaptations have refined these models. In information technology, for example, Venkatesh et al. (2003) developed the Unified Theory of Acceptance and Use of Technology (UTAUT), integrating earlier models to better predict IT adoption behaviour.

Conceptually, the field has broadened beyond motivation to also consider capability and opportunity. For instance, Michie et al. (2011) synthesised insights from 19 behaviour change frameworks into the COM-B model, arguing that behaviour (-B) results from interactions among capability (C), opportunity (O), and motivation (M).

In agriculture and forestry, the combined influence of conceptual extensions and sector-specific modifications can be observed. Farmers' and foresters' adoption decisions may be influenced by their perceived behavioural control (Dilotsotlhe & Duh, 2021). Technical capabilities, such as understanding complex digital tools or managing smart farming systems, may be essential (Eastwood et al., 2021).

Opportunities for adoption may be shaped by external factors such as financial resources and social environments (Despotovic et al., 2019; Feldman & Pentland, 2003). In addition, local and professional farming communities provide critical platforms for peer validation, which facilitates adoption (Rose et al., 2021).

Motivational factors include sector-specific incentives like yield improvements and input savings (Rose et al., 2021). In addition motivations linked to environmental stewardship, sustainability, and alignment with cultural or community values are also taken into account (Kallas et al., 2010; Jansen et al., 2020).

While these insights typically focus on downstream actors, we argue that the same behavioural, psychological, and contextual dynamics likely apply to upstream actors. For these actors, capabilities, opportunities, and motivations must also be considered, along with sector-specific strategic drivers. As Molner et al. (2019) argue, collaboration among upstream innovators is more likely when it helps clarify the technical core of an innovation, benchmark market potential, access resources, or align with downstream demand.

The main messages of this section for the 4Growth project are:

- Understand that innovation adoption is shaped by a combination of behavioural, psychological, and contextual factors, including capability, opportunity, and motivation.
- Recognise that adoption barriers and levers vary across the ecosystem and must be understood in both downstream and upstream contexts. While downstream actors are often influenced by practical and cultural factors (e.g., ease of use, cost savings, sustainability goals), upstream innovators are motivated by strategic considerations such as clarifying technical value, benchmarking potential, and aligning with market needs. Both sides require targeted support to enable ecosystem-wide diffusion.

12 Innovative Monitoring of an Ecosystem

12.1 Different methods of innovative ecosystem monitoring

Innovative monitoring techniques that are designed to analyse raw and processed data from activities in real time or over time, include automated data extraction through APIs and advanced text analysis using large language models (LLMs).

API-based Data Extraction

APIs offer alternatives to more traditional webscraping, which is often fragile due to the heterogeneity of website structures. APIs enable systematic, scalable extraction of structured data, such as weather forecasts, satellite imagery, soil measurements, and pricing information. Applications include, for example, the Sentinel Hub API provides real-time satellite imagery to monitor crop health and forest cover dynamics (Claverie et al., 2018), the USDA APIs offer agricultural data on commodity prices and planting statistics (USDA, 2023). Other applications include extracting product specifications (e.g., seed varieties, fertilizers) from supplier websites to track innovations, mining metadata and full-texts from scientific publications (e.g., Europe PMC, Crossref) to identify research gaps (Leip et al., 2019), and structuring communications from email archives. For instance, Molner et al. (2019) analysed email communication systems of a research institute to explore upstream technological orientation.

Large Language Models

Large Language Models (LLMs) can support the processing of extensive textual data in ecosystems. For example, they can assign sentiment scores to survey responses, news reports, and regulatory drafts, enabling detection of dissatisfaction, support, or concerns among actors (Kamilaris & Prenafeta-Boldú, 2018). Current applications include Talkwalker and Sprout Social (Inc., 2024; Sprout Social, 2024). A more general application is a platforms, such as YouScan that can also offer predictive insights based on social media activity (YouScan, 2024). LLMs can also categorise qualitative inputs from ecosystem actors, such as digiproduct users, digiproducers, etc., such as clustering appraisal results into opportunities and constraints (Sutherland et al., 2019). Additionally, by analyzing policy documents, project reports, and scientific articles, LLMs can automatically identify and group relevant collaborators based on thematic focus areas (e.g., soil health advocacy vs. precision farming promotion).

Within the 4Growth project, innovative monitoring techniques are developed in Task 2.2 Digital Agriculture & Forestry Uptake Grid, and disseminated to the observatories via Task 4.2: Data Collection through Observatories. More precisely, the 4Growth partner VTT has conducted automated data collection through web-scraping, focusing on forestry sector companies identified via the Statistical Classification of Economic Activities in the European Community (NACE) codes. This process involves designing prompts, identifying digital technologies on company websites, and transforming selected survey questions into prompts for AI analysis. Generative AI and Large Language Models are then applied to analyse the scraped content, yielding insights and lessons that will be further detailed in the upcoming Deliverable 4.8: Synthesis of Observatory Findings – Draft 1.

12.2 Benefits and drawbacks of innovative monitoring techniques

Innovative monitoring methods offer many advantages in terms of speed, repeatability, and independence, but they also pose challenges such as costs, dependence on technology, and data privacy, which must be addressed for successful and widespread implementation.

Benefits compared to traditional approaches
AI-based methods can help to mitigate survey fatigue, a common issue where respondents are overwhelmed by frequent or lengthy surveys, leading to low response rates (Sinickas, 2007). Furthermore, the innovative monitoring techniques can save time and are easy to replicate over multiple years, making it easier to track long-term trends. Additionally, these techniques allow for real-time or near-real-time data collection, providing quicker insights compared to surveys, which often take time to gather, process, and analyse. They also avoid issues related to low response rates, which often require extra time and effort to gather sufficient data in survey-based methods. Furthermore, innovative monitoring allows for the entire ecosystem to be monitored rather than relying on a sample, increasing the accuracy and comprehensiveness of the analysis.

Drawbacks compared to traditional approaches
These relatively new methods, however, also have several drawbacks compared to classical techniques such as surveys. For instance, the setup costs of advanced monitoring techniques are often higher than those of classical methods like a survey. A survey can be relatively easily set up without requiring too much technical knowledge, whereas advanced monitoring generally requires technical expertise (Culotta and Cutler, 2016). Additionally, these methods are highly dependent on technological infrastructure and involve a certain level of complexity in management. While these methods can collect vast amounts of data from various sources, the integration, processing, and analysis of this data can sometimes be complex (Kinne and Lenz, 2021). Furthermore, the use of automated AI-driven monitoring can raise ethical concerns. Issues such as consent, oversight, or the use of personal data within these technologies can also arise.

12.3 Top-down and bottom-up monitoring

In this study, we distinguish between two types of ecosystem monitoring, namely, top down and bottom up.

Top-down monitoring

Top-down ecosystem monitoring is characterised by its macro-level approach, focusing on highly aggregated data. An example of a top-down monitoring approach is macroeconomic modelling using aggregated ecosystem statistics (Rahimi & Sheffrin, 2003). This approach allows ecosystem monitoring with relatively low data intensity at low levels of detail, often available from open-source platforms where country-level sector statistics are reported.

Bottom-up monitoring

In contrast, bottom-up monitoring is a micro-level approach, focusing on individuals or firms, and requires vastly more difficult to obtain data at a rather high level of detail. Examples of bottom-up monitoring include surveys, analyzing company sales, and collecting user metrics (Bowen & Chen, 2001; Viswanathan, Sridharan, Ritchie, Venugopal, & Jung, 2012). This approach can be effective in obtaining a deeper understanding of why a certain technology is or is not adopted. It also allows explaining the possible heterogeneity of adoption, such as differences between gender, cultural values, and education. However, bottom-up approaches can be costly due to their time-consuming data collection aspect (Vreuls, Thomas, & Broc, 2009).

Combining top-down and bottom-up

Combining top-down and bottom-up methods can provide a more comprehensive and accurate ecosystem analysis by cross-validating macro and micro perspectives (Rivers & Jaccard, 2005). For example, a comprehensive customer survey (bottom-up) can be combined with macroeconomic modelling (top-down) to obtain a more complete picture of actual ecosystem dynamics. Thus, these different perspectives can be good complements to each other. The ingestion of both individual survey-level data and macroeconomic into 4Growth's Ecosystem Monitoring and Forecasting Tool (MMFT) is an example of this hybrid approach.

The main messages of this section for the 4Growth project are:

- Recognise that innovative monitoring techniques, such as API-based data extraction and large language models (LLMs), enable comprehensive and scalable analysis of digital ecosystems.
- Acknowledge that while these techniques offer significant benefits, including reduced survey fatigue, faster trend detection, and broader coverage, they also come with challenges. These include higher setup costs, technical complexity, and ethical concerns related to data privacy, consent, and transparency.
- Understand that innovative monitoring can follow either top-down or bottom-up approaches, each with specific advantages and trade-offs. Top-down methods provide high-level, aggregated insights using macro data, whereas bottom-up approaches yield detailed, actor-specific understanding but require more resource-intensive data collection.

13 Forecasting Adoption and Collaboration in an Ecosystem

One of the challenges in innovation management is forecasting the adoption or collaboration of innovations before their usage data becomes available. However, by combining intention-based data, analogical reasoning, and cross-ecosystem analysis, it is possible to make informed predictions about future adoption and collaboration patterns (Bass, 2001).

Estimating the potential size of an ecosystem often begins with intention surveys, which ask prospective users about their likelihood of adopting a given innovation. While such self-reported measures are imperfect, they serve as early indicators of market interest and can guide strategic planning.

To predict the pace of adoption or collaboration, analogical reasoning is often employed. This involves comparing the current innovation to similar technologies introduced in the past and drawing parallels in terms of adoption speed.

A distinctive feature of digital and data-driven innovations is their embeddedness in both digiproduct and data ecosystems. This dual presence enables cross-ecosystem inference. For example, hardware adoption can be used as a proxy for estimating platform engagement in associated data services. Conversely, usage patterns in data platforms, such as dashboard interactions or API calls, may reveal constraints or accelerators that shape future digiproduct adoption.

The main message of this section for the 4Growth project is:

- Understand that forecasting adoption and collaboration in digital ecosystems can be approached by combining intention surveys, analogical reasoning, and cross-ecosystem analysis to predict innovation uptake before usage data becomes available.

14 Conclusion

This study for the 4Growth project proposes that leveraging the concept of digital ecosystems offers a substantially more effective framework for analyzing the uptake of digital and data-driven innovations in agriculture and forestry than traditional market-based models. Digital ecosystems encompass a diverse and interconnected network of actors and subsystems, including both digiproduct ecosystems (centered on digitalised tools and services) and data ecosystems (focused on the generation and use of data to create value). Recognizing these overlapping structures helps us better understand how value is created, exchanged, and regulated within increasingly complex innovation environments.

One key contribution of this study is the expansion of the actor landscape. Adoption dynamics are not limited to digiproducers and digiproduct users but include collaborators, data intermediaries, and peripheral data users. The concept of social data externalities further underscores why innovation impacts extend far beyond direct users. Data generated by one actor often influences others in unforeseen ways, reinforcing the idea that digital and data-driven solutions have ecosystem-wide effects that go beyond merely serving individual user needs.

We introduced the concept of ecosystem space to describe the networked environment in which digital innovation unfolds. This space is dynamic, reflecting the shifting roles, relationships, and interactions among actors as innovations evolve across the product life cycle. Within this space, actors engage in ecosystem scoping, i.e. strategic activities through which they define their position, identify collaborators, and shape their value propositions. Unlike traditional market scoping, ecosystem scoping includes non-monetary dimensions such as access to data, knowledge, and influence. Importantly, ecosystem scoping is actor-specific: different actors perceive and engage with the ecosystem according to their goals, resources, and constraints. This diversity calls for flexible policy instruments that support varied engagement strategies.

To enhance engagement planning, we introduced the PARATA principle, an adaptation of the TAM–SAM–SOM model tailored to ecosystem contexts. By distinguishing between Potential Actors (PA), Relevant Actors (RA), and Targetable Actors (TA), the PARATA model helps clarify who could be involved, who should be involved, and who can realistically be influenced or supported. Within the targetable segment, distinguishing between innovating actors, who initiate and co-develop solutions, and imitating actors, who follow based on peer behaviour, is essential for shaping adoption strategies. Moreover, recognizing that actors may shift roles over time, such as moving from peripheral data user to active collaborator, adds further complexity to adoption forecasting and engagement planning.

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