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INTRODUCING THE AGRIFOOD SYSTEMS TECHNOLOGIES AND INNOVATIONS OUTLOOK (ATIO)

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Food and Agriculture Organization of the United Nations
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FOREWORD

Today, our world is facing complex challenges, including conflicts, humanitarian emergencies, the impacts of the climate crisis and the COVID-19 pandemic – causing economic shocks and downturns, and interruption of international supplies. These crises are contributing to the dramatic increase in world hunger and inequality and causing the living standards of the most vulnerable populations to drastically deteriorate. As the planet warms and natural resources become scarce, our efforts to achieve the Sustainable Development Goals (SDGs) are at risk.

The FAO Strategic Framework 2022–2031 reflects our full commitment to the 2030 Agenda for Sustainable Development and details the reasons why it is vital that agrifood systems are transformed towards more efficiency, inclusivity, resilience and sustainability. Only through transformation can there be better production, better nutrition, a better environment and a better life for all: the *four betters*. However, it will not be easy to produce more food while reducing inputs and keeping pace with increasing demand, and simultaneously addressing the many issues that currently represent barriers to affordable, healthy diets, livelihood opportunities and elimination of poverty and hunger.

Transformation of agrifood systems will only be possible through mindful application of science, technology and innovation (STI). Indeed, STI are crucial elements of my vision for a reinvigorated FAO, and are instrumental in building a better future. The recent FAO Science and Innovation Strategy reinforces the application of science and innovation across the Organization's technical work and normative guidance it provides.

However, the uptake of technologies and innovations in many low- and middle-income countries is currently suboptimal. A key component to rectifying this weakness will be a new knowledge product, the *Agrifood Systems Technologies and Innovations Outlook (ATIO).* This biennial publication, produced by FAO and its partners, will curate up-to-date information on the global state of STI. It will supplement valuable data curation with horizon-scanning and foresight about the impact pathways that various STI under development might follow, and with syntheses of the available evidence on STI impacts. ATIO will report on data and analyses from numerous sources to become a flagship publication that will aid agrifood systems decision-makers around the world.

There are insufficient data and scientific analyses for the numerous contributing components of agrifood systems and how application of STI can help address this deficiency. ATIO represents a major contribution, and I hope that it will become a valuable tool in the endeavour to create a more equitable world. This report introduces ATIO and sets forth what will be necessary for ATIO to fulfil its role.

Qu Dongyu
FAO Director-General

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ABBREVIATIONS AND ACRONYMS

3ie	International Initiative for Impact Evaluation
AFS	agrifood systems
AI	artificial intelligence
ASTI	Agricultural Science and Technology Indicators
ATIO	Agrifood Systems Technologies and Innovations Outlook
CoSAI	Commission on Sustainable Agriculture Intensification
DEI	diversity, equity and inclusion
DIME	World Bank's Development Impact Evaluation group
EPO	European Patent Office
GDP	gross domestic product
GII	Global Innovation Index
GINA	Global database on the Implementation of Nutrition Action
GPS	Global Positioning System
HDI	Human Development Index
HERS	healthy, equitable, resilient and sustainable
HICs	high-income countries
HLPE	High Level Panel of Experts
IFPRI	International Food Policy Research Institute
IFSS	Innovative Food Systems Solutions
InSTePP	International Science & Technology Practice & Policy
ISAAA	International Service for the Acquisition of Agri-biotech Applications
ISNAR	International Service for National Agricultural Research
LMICs	low- and middle-income countries
ML	machine learning
NASA	National Aeronautics and Space Administration
NER	named-entity recognition
NLP	Natural Language Processing
PCT	Patent Corporation Treaty
R&D	research and development
RCT	randomized controlled trial
RFT	Readiness for Frontier Technologies
SME	small- and medium sized enterprise
SPEED	Statistics on Public Expenditures for Economic Development
SPIA	Standing Panel on Impact Assessment
STI	science, technology and innovation
SYREAF	Systematic Reviews for Animals & Food
TASAI	The Africa Seed Access Index
TASAI	The Africa Seed Access Index
TFP	Total factor productivity
UNCTAD	United Nations Conference on Trade and Development
WCRF	World Cancer Research Fund
WIPO	World Intellectual Property Organization

GLOSSARY

Agrifood systems (AFS) encompass the entire range of actors, and their interlinked value-adding activities, engaged in the primary production of food and non-food agricultural products, as well as in storage, aggregation, post-harvest handling, transportation, processing, distribution, marketing, disposal and consumption of all food products including those of non-agricultural origin.

Agricultural innovation is the process whereby individuals or organizations bring new or existing products, processes or ways of organization into use for the first time in a specific context in order to increase effectiveness, competitiveness, resilience to shocks or environmental sustainability and thereby contribute to food security and nutrition, economic development or sustainable natural resource management (FAO, 2019).

Horizon-scanning involves seeking and researching signals of change in the present and their potential future impacts.

An **indicator** is a measure that reflects the state or level of a phenomenon of interest.

Innovation involves doing something new and different, whether solving an old problem in a new way, addressing a new problem with a proven solution, or bringing a new solution to a new problem.[1] Types of innovation include technological, social, policy, institutional and financial innovations, as well as adaptation of longstanding (e.g. indigenous) methods to larger-scale applications, as with some sustainable agricultural approaches (e.g. agroecology). In the context of agrifood systems (AFS), innovation is used as a verb (to innovate), referring to the process by which individuals, communities or organizations generate changes in the design, production or recycling of goods and services, as well as changes in the surrounding institutional environment, that are new to their context and foster transitions towards sustainable AFS for food security and nutrition. Innovation is also used as a noun to refer to the changes generated by this process. Innovation includes changes in practices, norms, markets and institutional arrangements, which may foster new networks of food production, processing, distribution and consumption that may challenge the status quo (HLPE 2019).

Science signifies the enterprise whereby humankind, acting individually or in groups, makes an organized attempt, by means of the objective study of observed phenomena and its validation through sharing findings and data and through peer review, to discover and master the chain of causalities, relations or interactions; brings together in a coordinated form subsystems of knowledge by means of systematic reflection and conceptualization; and, thereby furnishes itself with the opportunity of using, to its own advantage, understanding of the processes and phenomena occurring in nature and society.[2] As stated by the Committee on Economic, Social and Cultural Rights, other systems of knowledge and ways of knowing coexist with science, including local, traditional and indigenous knowledge, and have an important role to play in the global scientific dialogue.[3]

Scenarios are the multiple stories or models of the future that one uses to explore alternative prospective paths and the multiple plausible future impacts of a current intervention.

Technology involves the application of science and knowledge to develop techniques to deliver a new product and/or service or to use a new process to deliver an established product or service.[4] Technologies sometimes emerge serendipitously but are more commonly purposefully developed and are therefore embedded in, and have influence on, social, economic and environmental relations.

1 UN Innovation Toolkit, 2019. https://www.uninnovation.network/un-innovation-toolkit

2 UNESCO Conference, Recommendation on Science and Scientific Researchers, 2017 (paragraph 1.a.i)

3 Committee on Economic, Social and Cultural Rights, General comment No. 25 on science and economic, social and cultural rights in the International Covenant on Economic, Social and Cultural Rights, 2020 (paragraph 39)

4 Adapted from A/74/238. Agriculture technology for sustainable development. Report of the Secretary-General. Seventy-fourth session.

EXECUTIVE SUMMARY

It is increasingly widely recognized that the world must accelerate and reorient transformation towards more efficient, inclusive, resilient and sustainable agrifood systems (AFS) for better production, better nutrition, a better environment and a better life, leaving no one behind, as emphasized in the FAO Strategic Framework 2022–2031. The *four better*s reflect the interconnected economic, social and environmental dimensions of sustainable development intrinsic to AFS, which incorporate not just primary production from farms, fisheries and forests, but also the manufacturing and services that account for more than 70 percent of the value added in consumer food expenditures, the nutrition and health impacts of consumers' diets, and feedback effects on the natural environment that support all human and natural functions throughout AFS. The goal of AFS transformation is to produce more food with fewer inputs to meet impending growth in demand while simultaneously ameliorating or even reversing AFS' adverse environmental impacts on climate, biodiversity, forests, soils and water, reducing food loss and waste as well as prices to enhance access to affordable, healthy diets, creating new livelihood opportunities and promoting social inclusion to eliminate extreme poverty.

AFS transformation to deliver the *four betters* requires increased attention to developing, adapting and diffusing impactful science, technology and innovation (STI). Current levels and patterns of STI uptake are inadequate to facilitate needed AFS transformations, especially in low- and middle-income countries (LMICs). Moreover, the descriptive and evaluative evidence on current and emergent AFS STI is also insufficiently well understood to permit intentional management of STI to meet the multiple objectives of future AFS: efficient, inclusive, resilient and sustainable. This is especially true with respect to technological, social, policy, financial and institutional innovations that are necessary to unlock the potential of engineering- and science-based technologies. Given the long lead times inherent to the impacts of STI on society, redirecting STI to do more than reinforce past patterns requires immediate action.

This report introduces the vision, rationale, scope and methods for new knowledge products FAO will launch as part of a new *Agrifood Systems Technologies and Innovations Outlook (ATIO)*. ATIO will be a major undertaking, a path-breaking initiative led by FAO, supported by several key partners globally. ATIO will be an iterative process to develop a new, biennial FAO publication supported by occasional, focused, supplemental publications and a regularly updated open access database. The objective of ATIO is to curate existing information on the current, measurable state of science, technology and innovation (STI) and upcoming changes, as well as their transformative potential, to inform evidence-based policy dialogue and decisions, including on investments. Policymakers and their advisers, along with the public, private and philanthropic investors who finance AFS STI research and development (R&D), need clear, non-technical messages supported by strong scientific evidence, including open access data for decision-making and investment planning. But data and analyses are currently broadly scattered, and difficult to synthesize and access for decision-makers who need a comprehensive view of the full AFS, spanning the present state and future prospects. ATIO will pull together existing data and analyses from myriad sources into an integrative, actionable body of evidence for key decision-makers throughout AFS and around the world. This will necessarily take time to identify, standardize, negotiate open access to, and subsequently curate data sources to make them actionable while ensuring the data's high quality.

In doing so, ATIO will also call attention to important data and evidence gaps that may merit concerted new efforts. ATIO will be useful for advocacy – e.g. for more or different forms of AFS R&D investments, and for institutional and policy reforms – and can help guide prioritization by private and public sector entities. The hope is that ATIO becomes a central periodical reference and open access data source on how science, technologies and innovations can and do change current AFS, transforming them to become more efficient, inclusive, resilient and sustainable. Perhaps most importantly, ATIO will tap FAO's unsurpassed convening capacity around AFS globally to help drive productive societal conversations on the role of STI in transforming AFS, enhancing inclusion and transparency in the one socioeconomic sector on which every human depends each day.

The distinguishing feature of ATIO will be the development of knowledge products that together provide end-to-end life cycle coverage of AFS STI throughout the world. The STI life cycle is divided into four key stages. The most upstream stage concerns STI inputs, the investments, personnel, policies and other factors that generate new STI. The second stage of pre-emergent STI is when basic and applied scientific advances develop new ideas, materials, methods and processes that show promise but have not yet been released for uncontrolled use in the real world. The third stage, emergent STI, refers to the period once new STI begins to emerge in day-to-day use by AFS agents and enterprises outside researchers' control, but the STI remains sufficiently novel that no systematic accounting for its diffusion is in place yet. The final stage, of mature STI, relates to established STI that have been in real world use sufficiently long and widely that systematic tracking of diffusion should be feasible. Many mature STI eventually become obsolete, displaced by a subsequent generation of STI as it matures.

Each STI life cycle stage demands distinctive data collection, analysis and curation methods and involves different evidence synthesis methods for impact evaluation. ATIO will track a new technology or innovation once its adaptation or combination into AFS becomes apparent in the scientific and industry literatures, if only as a hypothesized application domain, or in real world practice. The challenge is that ATIO only curates and analyses pre-existing data – it does not involve any *de novo* primary data collection – and so must rely on existing data systems. Thus, another valuable function of the broader ATIO-based knowledge product line is to identify key evidence gaps that might be filled through new primary data collection systems that could then feed into ATIO. A thorough review of data sources that satisfy a set of key inclusion criteria indicates, for example, how little systematic data and evidence exist around farmer-led innovations, around social and policy innovations – as distinct from science- or engineering-based technologies – and around the intermediate and consumer-facing stages of agrifood value chains. ATIO can thereby inform not only investment and policy decisions, but equally data collection and analysis choices by research and policy organizations.

The appeal of a product that provides comprehensive end-to-end life cycle coverage of AFS STI also poses a major challenge. The inventory of existing, suitable STI input and mature STI datasets that meet key inclusion criteria is relatively short, and especially thin on post-farmgate technologies, and financial, institutional, social and policy innovations relative to primary production technologies based on the natural sciences and engineering, and rarely includes STI that originates outside more formal research channels. ATIO can help expand, standardize and update coverage of key indicators, providing an improved dashboard to help public, private and philanthropic organizations navigate the AFS challenges and opportunities ahead. Furthermore, existing datasets focus heavily on the first and final stages – STI inputs and mature STI – with notable gaps surrounding pre-emergent and emergent AFS STI. Accelerating AFS transformation requires paying considerably more attention to these critical intermediate stages, not least to help shorten the appreciable lags from initial R&D investments to scaling impactful new STI among AFS actors globally. Finally, few syntheses exist of the available impact assessment evidence on AFS STI, and they are difficult to find.

ATIO will also serve as a key evidence synthesis host for AFS STI impact assessments, starting from the *ex ante* assessments of pre-emergent technologies through the *ex post* impact evaluations of emergent and mature STI, both individually and as bundles customized to specific AFS contexts. ATIO will provide a portal that encompasses scoping and systematic reviews, and statistical meta-analysis, i.e. of the body of impact evaluation evidence that sheds light on what is expected to or has been proven to work, where, and under what conditions. Such data are among the most useful for resource-constrained agencies, perhaps especially those operating in LMICs. ATIO can also help identify key evidence gaps that urgently need impact assessments to generate actionable evidence syntheses, thereby helping identify key under-supplied international public goods.

Each ATIO edition will be developed over a two-year cycle, published as a biennial publication. Once the core ATIO team, protocols and electronic platforms are established and the inaugural edition published, there might be supplemental editions between the regular ones, tackling key ancillary questions in a shorter format. Open access data and evidence synthesis portals will be frequently updated each year.

As a specialized agency of the UN that leads international efforts to defeat hunger, FAO bears special responsibility for helping inform and advise public and private decision-makers to accelerate necessary AFS transformation globally, especially in LMICs. Today's AFS will unquestionably transform, but the pace, directions and impacts of transformation can and should be influenced by actionable evidence. Currently, the world lacks sufficiently integrated, high-quality data and scientifically vetted analyses across the AFS STI life cycle and with global coverage to help foster constructive policy dialogue, and induce urgently needed increased investment in AFS STI, especially for LMICs. ATIO represents a major contribution in that direction.

GUYANA
Herman Phillips, 63, has lived his whole life in the Rupununi region based on a subsistence existence. He believes that is his natural right as an Indigenous Person in the Rupununi. He fishes, uses his bow and arrow, nets and lines, and he hunts in the forest.

CHAPTER 1
WHY AN ATIO?

For at least 10 000 years, humans have been altering nature to produce more food in the pursuit of improved lives and livelihoods for a growing population, with great agronomic and economic success. Global agricultural output has increased approximately fourfold over the past half century, far outpacing human population growth, while total factor productivity (i.e. output per unit input) has roughly doubled over the same period, despite the considerable headwinds of climate change (Keating *et al*., 2014; Ortiz-Bobea *et al*., 2021). Had the Green Revolution of the 1960s–1980s never happened, the best estimates suggest that per capita incomes in the developing world would today be only half of their current levels (Gollin *et al*., 2021). The approximately USD 60 billion invested over the last half century in research and development (R&D) by CGIAR, the global network of agricultural research centres, has delivered an estimated benefit/cost ratio of ten or more, far surpassing returns on most other investments (Alston *et al*., 2022). Huge economic and agricultural productivity gains have come not just from biophysical and engineering advances but equally from institutional and policy innovations that stimulate human, natural, physical and social capital accumulation, and that reduce risk, barriers to exchange, and the concentration of economic and political power in the hands of a few (Acemoglu, Johnson and Robinson, 2005).

These gains have come at a growing cost, however, in the form of adverse spillover effects on climate, natural environments, public health and nutrition and social justice. Those unintended consequences of the almost-single-minded pursuit of agricultural productivity growth, as well as growing questions about the sustainability of agronomic and economic gains following a business-as-usual model, have fuelled growing calls for accelerated and reoriented agrifood systems (AFS) transformation. A series of high-level reports and meetings, culminating most recently in the 2021 UN Food Systems Summit, has called for addressing the pressing needs of people and the planet by accelerating transformation towards healthy, equitable, resilient and sustainable (HERS) AFS (GloPan, 2016, 2020; Haddad *et al*., 2016; IPCC, 2019; IPBES, 2019; Messerli *et al*., 2019; Willett *et al*., 2019; Herrero *et al*., 2020; FAO, 2021, 2022; HLPE, 2020; Barrett, 2021a; von Braun *et al*., 2021; Barrett *et al*., 2022a).

As the UN specialized agency for food and agriculture, the FAO Strategic Framework 2022–2031 therefore commits to support the 2030 Agenda for Sustainable Development through the “transformation to MORE efficient, inclusive, resilient and sustainable, AFS for *better production*, *better nutrition*, a *better environment*, and a *better life*, leaving no one behind” (FAO, 2021). The *four betters* reflect the interconnections intrinsic to AFS and the three pillars of sustainability (economic, social, and environmental). AFS encompass the entire range of actors, and their interlinked value-adding activities, engaged in the primary production of food and non-food agricultural products, as well as in storage, aggregation, post-harvest handling, transportation, processing, distribution, marketing, disposal and consumption of all food products including those of non-agricultural origin. AFS have a wide range of impacts, touching each Sustainable Development Goal (SDG) directly or indirectly (Herrero *et al*., 2021).

The strategic development and deployment of science, technology and innovation (STI) is a central enabling factor for AFS transformation and ultimately contributes to the 2030 Agenda for Sustainable Development and the three interlinked dimensions of sustainability (FAO, 2021). Existing STI are impactful, but there is a gap in their effective use, characterized by challenges of appropriateness, accessibility and affordability. Additional challenges in harnessing STI for AFS range from lack of information on the full array of technological, social, policy, financial and institutional innovations available, underinvestment in research and in key STI inputs, technology mismatch for many AFS small- and medium-sized enterprises (SMEs, which include small-scale producers and other under-resourced persons and enterprises), gaps in using science and evidence for decision-making, and insufficient information for policy prioritization in the low- and middle-income countries (LMICs).[5]

FAO recognizes that countries have diverse challenges, needs and capacities with respect to STI, including in relation to infrastructure, levels of education and technical capacities. At the same time, there are major common challenges at national, regional and global levels. Addressing these challenges requires the coordinated efforts of a range of actors, with FAO playing a key role in the provision of global public goods, knowledge, guidance, coordination and policy coherence. In this context, the FAO Science and Innovation Strategy (FAO, 2022) has been designed as a key tool to support the delivery of the Strategic Framework 2022–2031 (FAO, 2021).

One urgently needed coordinated effort concerns expanded, up-to-date monitoring and assessment of STI. Not only are current levels and patterns of STI inadequate to facilitate needed AFS transformations, the descriptive evidence on STI levels and patterns is insufficiently well understood to permit intentional management of STI to meet the multiple objectives of future AFS – efficient, inclusive, resilient and sustainable – especially in LMICs. Given the long lead times inherent to STI's impacts on society, redirecting STI to do more than reinforce past patterns requires immediate action. Monitoring progress towards the goal of AFS transformation therefore requires tracking the STI that drive systems transformations. But sufficiently integrated, high-quality data that track AFS STI and scientifically vetted analyses of the impacts of AFS STI are currently lacking or unintegrated across the full life cycle of STI, and those data that do exist are fragmented, incomplete, and often difficult to find in a rapidly expanding world of data. The data and analysis deficiencies are especially acute as regards innovations that do not originate from formal engineering and natural sciences-based research systems, including social, institutional and policy innovations, as well as discoveries that originate in indigenous knowledge or informal experimentation by farmers, entrepreneurs, communities, etc.

Hence the proposed new knowledge products, intended to provide end-to-end life cycle coverage of AFS STI. FAO's role is to support countries in identifying, piloting, and scaling technologies and innovations adapted to their needs and contexts, recognizing that this is particularly challenging due to the specific constraints faced by the vast number of the world's small-scale producers, including women. To support that role, FAO will develop and launch a new outlook focused on understanding better the level of uptake of technologies and innovations, entitled the *Agrifood Systems Technologies and Innovations Outlook (ATIO)*.

Several aspects of the proposed ATIO merit special mention. First, because STI's needs, priorities and capacities differ considerably across countries, an ATIO must track STI progress at national level. Moreover, because the most pressing AFS transformation must occur in today's LMICs, monitoring must pay special attention to LMICs. Income and population growth, with urbanization, are the main drivers of future increases in food demand growth. Given current and projected differences in those rates across world regions, and their lower initial levels of income, Asia is the near-term locus of most food demand growth (Fukase and Martin, 2020), while at longer horizons, out to the end of the century, half or more global food demand growth will occur in sub-Saharan Africa (Valin *et al.*, 2014; Barrett, 2021a; Barrett *et al.*, 2022a). Since more than 70 percent of food consumed originates from primary production in the country in which it is eaten (d'Odorico *et al.*, 2014), the geography of food demand growth necessarily compels transformation of entire AFS in LMICs, from primary production through

5 The World Bank's listing of LMICs was used, as defined at https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups.

processing and distribution to final consumer food environments.

A great deal of AFS STI originates in high-income countries (HICs) and flows into LMICs. The G20 nations currently account for about 90 percent of total research expenditures, publications, and patents and 80 percent of countries invest less than 1 percent of gross domestic product (GDP) in R&D, most of them LMICs (UNESCO, 2021). Moreover, innovations in HICs – e.g. private or public product standards that affect trade, political or popular opposition to specific new technologies – can affect markets and policies highly relevant to LMICs, even though trade volumes remain relatively small, in most years less than a quarter of all food consumed globally (d'Odorico *et al*., 2014). The cross-border impacts of STI necessitates looking at all countries globally, not solely at national-level conditions. Therefore, an ATIO must at once emphasize national level data, especially in the LMICs, where data challenges are especially acute (see section 4), as well as relevant STI wherever in the world it occurs.

Second, FAO does not propose a "state of …" report that offers only a stocktaking of descriptive evidence of AFS' current state. Assessments of the current state of AFS STI in individual countries are indisputably valuable and necessary. They are also surprisingly difficult to complete because of incomplete and inconsistent data (see section 8). But descriptions of the current, measurable state of STI are far from sufficient because transformative impacts emerge only with a considerable lag. AFS STI commonly takes one or two decades – or more – to develop from ideation through piloting to diffusion to achieve measurable impacts at scale (Alston and Pardey, 2021). To support the accelerators essential to scaling up prospectively impactful STI (Herrero *et al*., 2020; Barrett *et al*., 2022a), policymakers must anticipate coming changes and plan accordingly.

An ATIO must therefore go beyond the valuable data curation FAOSTAT currently does for current, observable states of mature STI or of investments in R&D intended to generate future mature AFS STI. An ATIO must supplement those familiar accounting activities with expanded data coverage of post-farmgate STI and financial, institutional, social and policy innovations for which we find few existing, high quality datasets. It is likewise essential to expand coverage to encompass horizon-scanning about pre-emergent and emergent STI and foresight about uncertain AFS futures and the impact pathways that various STIs under development might follow.

Horizon-scanning and foresight work is necessary because the complex interplay of human and natural systems, as well as the vastly decentralized and largely uncoordinated nature of decision-making throughout interconnected AFS, generate a vast array of prospective futures (Barrett *et al*., 2021a, 2022a). Foresight and scenario-based approaches help stakeholders explore those possible pathways towards achieving desired outcomes and avoiding undesirable ones (O'Neill *et al*., 2014; Fricko *et al*., 2017; Barrett *et al*., 2021a; Lentz, 2021; Zurek *et al*., 2021). An ATIO would therefore emphasize not only careful accounting for measurable inputs to developing impactful future AFS STI (section 5) – such as agricultural R&D investments – or for the diffusion of STI already in use. An ATIO must also identify, document progress on, and assess pre-emergent STI (section 6) and newly emergent STI (section 7) that pose even greater measurement challenges than do STI inputs or mature STI (section 8).

History has proved time and again that humans can radically alter the trajectory of AFS. But it is only possible to manage things that are monitored. The information that informs actions by key public and private sector players therefore matters. ATIO concentrates on curating high quality data to help inform decision-makers.

Third, the combination of the need for foresight and scenario analysis at national level, as well as global assessments, means that an ATIO must explicitly address the considerable heterogeneity that exists across AFS, among and within countries. This is especially true to attend to the needs of small-scale producers, women, and other marginalized groups. Their interests in STI are often overlooked, although they represent the bulk of AFS stakeholders, given both heavy dependence on agrifood value chain activities for livelihoods and the importance of food in the budgets of poor consumers. An ATIO must attend to the context-specificity and appropriateness of STI's predictable and observable – if sometimes unintended – suitability, adaptation and diffusion of STI, and the differential impacts, risks and unintended consequences of emergent STI within AFS. This necessarily requires paying attention to regulatory, ethical, gender, social, environmental and policy issues at national, regional and global levels.

1.1 A THEORY OF CHANGE FOR ATIO

ATIO is envisioned to be a key enabler for achieving the vision outlined in the FAO Science and Innovation Strategy (FAO, 2022). The overall objective of ATIO is to provide information on the current, measurable state of STI and likely upcoming changes, as well as their transformative potential, to inform evidence-based policy dialogue and decisions, including on investments. ATIO will track STI progress at national level and pay special attention to LMICs, where data challenges are particularly acute. The cross-border impacts of STI necessitates looking at all countries globally, not solely at national-level conditions, so ATIO will emphasize relevant STI wherever in the world it occurs.

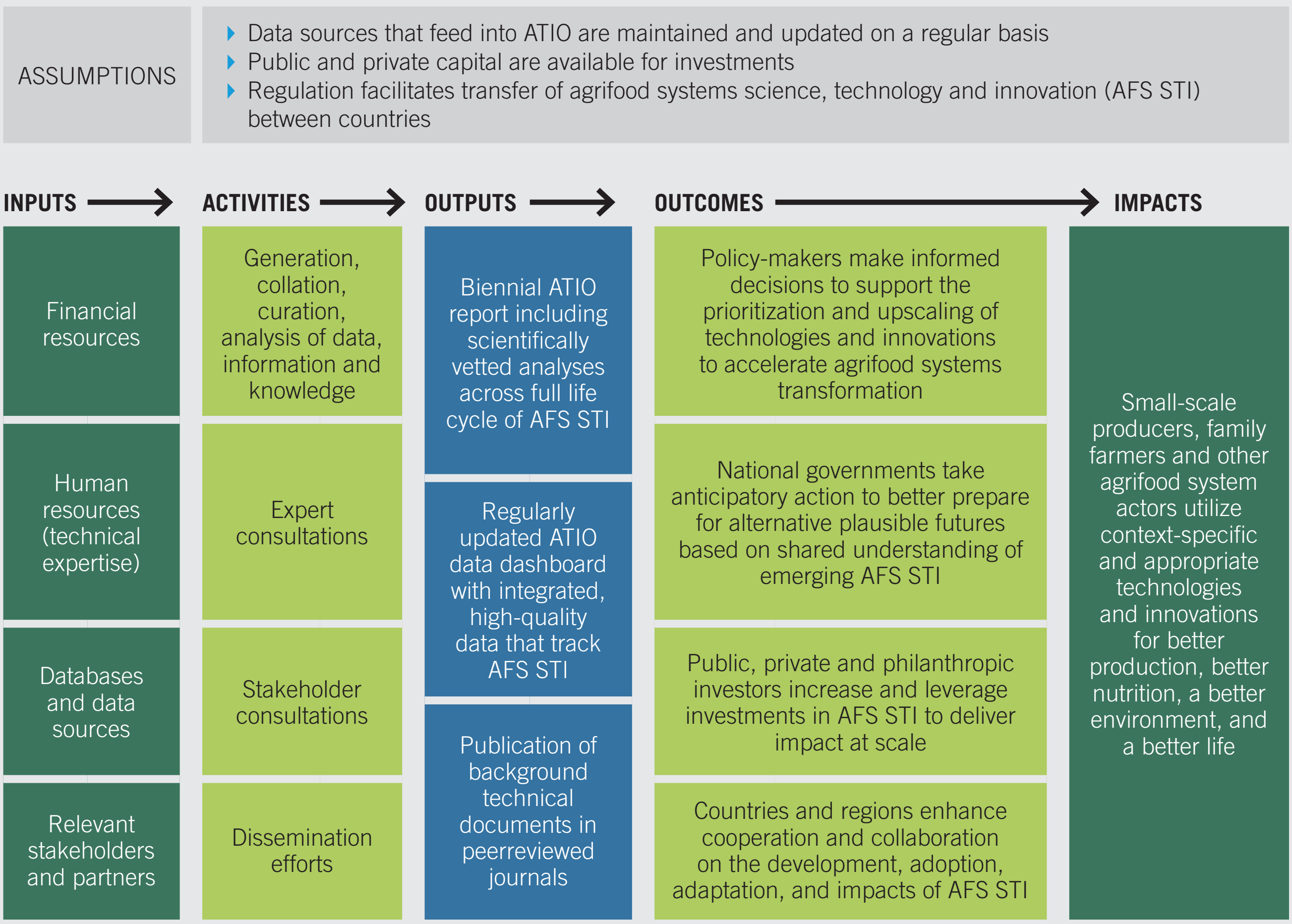
Well-informed decisions require indicators throughout the AFS STI life cycle, from the initial investments – in R&D funds, scientific personnel and material resources (like laboratories, genetic collections, farmers and farmer-based platforms such as farmer field schools or science and technology backyards) – through the refinement and adaptation of initial ideas, through their initial piloting, emergence and scaling into mature STI diffusing widely, at least in some places. ATIO will provide policymakers, research managers, donor organizations, civil society and private sector stakeholders with reliable and up-to-date open data on an ongoing basis. This will include information on the status, directions and impacts of AFS STI at various stages of readiness, and prospective future changes in global/regional/national agrifood STI patterns to facilitate the identification of key gaps and neglected areas, as well as set future investment priorities. ATIO will supplement valuable data curation with horizon-scanning about pre-emergent and emergent AFS STI, with foresight about the impact pathways that various STIs under development might follow, and with syntheses of the available evidence on STI impacts. Such analyses will help engage stakeholders in meaningful discussions to come to a shared understanding of AFS STI and their possible future directions.

ATIO will coordinate and curate data, evidence syntheses, expert elicitations, and peer-reviewed technical research to collectively generate a user-friendly body of data and analysis to better inform stakeholders who seek to employ STI to accelerate AFS transformation. It will also help foster South–South and Triangular collaborations around STI. In addition to the value of ATIO's outputs, the research process required to produce and update ATIO can enhance expert engagement with key stakeholders, helping build awareness of AFS STI issues and stimulate greater investment and action to make AFS more efficient, inclusive, resilient and sustainable.

ATIO's theory of change outlines how ATIO can contribute to accelerating global AFS transformation, especially in LMICs, help stakeholders overcome constraints vis-à-vis STI data availability, analysis, visibility, coordination, and expert access, and determine what outcomes will contribute to this transformation (see Figure 1).

ATIO's impact pathways are mediated by efforts to ensure that the contents of the regular report, the regularly updated data, and the peer-reviewed technical background materials developed as part of the ATIO process – collectively, the outputs from ATIO that foster change – are accessible and usable, and that potential users are aware of how to use the products, their strengths and limitations. Direct dissemination efforts of data and publications, stakeholder consultations and expert consultations will provide specific, time-bound processes to translate ATIO products into outcomes, while the data dashboard will provide an on-demand digital resource available to stakeholders at their convenience.

FIGURE 1 A THEORY OF CHANGE FOR ATIO



The ATIO will contribute to all three pillars of the FAO Science and Innovation Strategy:

PILLAR 1

Strengthening science and evidence-based decision making.

PILLAR 2

Supporting innovation and technology at regional and country level.

PILLAR 3

Serving Members better by reinforcing FAO's capacities.

ATIO will contribute directly to Pillar 1 through improved data collection and curation for informed decision-making, knowledge on emerging technologies and innovations, and engagement with stakeholders and actors within the AFS innovation ecosystem. ATIO activities will contribute to Pillar 2 by supplying crucial inputs to support the development and uptake of technologies and innovations at the national level and enhance synergies among regions through mutual learning and interregional cooperation on key issues of common interest. ATIO will contribute to Pillar 3 through boosting knowledge management, dissemination efforts and consultations with stakeholders and experts to build and improve collaborative networks within and among key AFS actors and the broader public.

Achieving these outcomes and impacts will require substantial complementary efforts and investments beyond ATIO. Many factors will need to be in place (assumptions in theory of change language) for ATIO data collection efforts to contribute ultimately to targeted outcomes and desired impacts. These factors include internal factors such as data sources that feed into ATIO and are maintained and updated on a regular basis, as well as external factors such as available public and private capital for investments and appropriate regulatory environment exists to facilitate transfer of AFS STI between countries. This would ensure that the innovation landscape is enabled at various scales (regional, national, subnational, etc.). It also assumes that decision-makers will thoughtfully consider and act on the evidence collected and generated through ATIO.

So why should FAO invest in a regular ATIO product? Because as a specialized agency of the UN that leads international efforts to defeat hunger, it bears special responsibility, and has unparalleled convening capacity, to integrate and develop data sources and analyses of those data that might helpfully inform public and private decision-makers. Today's AFS will unquestionably transform, but the pace, directions and impacts of transformation can and should be influenced by actionable evidence. Currently, the world lacks sufficiently integrated, high-quality data and scientifically vetted analyses across the AFS STI life cycle to help foster constructive policy dialogue, and induce urgently needed increased investment in AFS STI, especially for LMICs. An ATIO can make a useful contribution in that direction.

SENEGAL
Men and women from the community work in the tree nursery created in the village as part of the Great Green Wall Initiative.

CHAPTER 2
ATIO BOUNDARIES AND SCIENCE, TECHNOLOGY AND INNOVATION COVERAGE FOR AGRIFOOD SYSTEMS TRANSFORMATION

An ATIO cannot tackle everything. Boundaries must be drawn thoughtfully. Three key areas are considered where boundaries need to be drawn.

First, an AFS focus is needed. There already exist respected products that review the general state of science, technology and innovation across countries, such as the usually biennial OECD Science, Technology and Innovation Outlook (OECD, n.d.), the United Nations Conference on Trade and Development's (UNCTAD) triennial Technology and Innovation Report (UNCTAD, n.d.), the usually quinquennial UNESCO Science Report (UNESCO, n.d.), and the annual WIPO Global Innovation Index (WIPO, n.d.). Because the sponsor agencies have society-wide mandates, however, those reports rarely focus on AFS (see Box A). While those reports are certainly relevant, as tomorrow's AFS STI often originates in other sectors (Moser, 2021), the scale and centrality of AFS to the SDGs and longer-run societal objectives favours creation of a regular ATIO product that focuses more tightly on STI developed expressly to address AFS opportunities/challenges, especially those of today's LMICs, given their especially heavy economic dependence on AFS.

In the interests of focus, it is proposed that a new technology or innovation only enters an ATIO once its adaptation or combination into AFS becomes apparent in the scientific and industry literatures, if only as a hypothesized application domain. For example, had an ATIO existed in the 1970s, it would not have covered classified, space-based radionavigation technologies used only by the United States military before the US government released that global positioning system (GPS) technology for commercial use.[6] Rather, an ATIO would pick up precision agricultural machinery and digital network management technologies as they first appear in the scientific and industry literature (including in essays mooting new prospective uses for GPS, and in patent filings and venture capital databases) before they emerge into active, open use by farm equipment and food distribution companies. An ATIO would then track their emergence, adaptation – e.g. into consumer-facing food delivery apps – and diffusion as they become mature technologies. ATIO must be routinely engaged in horizon-scanning to identify STI as it begins to cross into purposeful incorporation into AFS.

Second, an ATIO must expand beyond the domain of the natural sciences and engineering to encompass social and economic science-based STI in policies and institutions. Throughout this report, references to STI imply this more expansive definition. AFS transformation is a fundamentally transdisciplinary endeavour. Today's AFS challenges and opportunities have anthropogenic origins, i.e. they stem directly from human consumption, exchange and production behaviours and different values and perceptions. Human behaviours shape and are shaped not only by natural processes or engineering advances, but also by culture, institutions, and policies that create sociopolitical constraints and cultural or economic incentives for or against specific actions. Indeed, the great challenge of AFS transformation is that it requires decentralized actions by billions of individual actors. Public policymakers and private enterprises can influence behaviours, but they cannot control them. Changes to policies, institutions, and culture are among the key tools leaders use to influence behaviours.

An ATIO must therefore report on innovations beyond just new technologies based on engineering

6 Roblin (2017) offers a short, fascinating account of how the tragic loss of Korea Airlines flight 007 in 1983 helped accelerate the release of GPS technologies for broad commercial adaptation globally.

or natural sciences, to include a wide diversity of transformative social, policy, institutional, financial and cultural innovations. This in no way diminishes the crucial importance of advances in agroecological, biochemical, digital, mechanical, and other natural sciences- and engineering-based domains. Rather, it recognizes that such innovations only succeed when bundled with complementary innovations in institutions, markets or policies that facilitate diffusion (Barrett *et al.*, 2022a). As AFS transformation encompasses an enormous range of human activities and organizations, these social innovations need to be tracked and studied – and promoted, in the case of those demonstrated as effective in advancing the broad goals of AFS transformation – alongside and on an equal footing with more familiar STI rooted in engineering and the natural sciences. Unfortunately, AFS STI data collection systems have historically focused on measurable scientific and financial indicators, with little systematic collection of data on institutions or policies, as subsequent sections will document. ATIO can help spark increased attention, and systematic high quality data collection, to fill that important lacuna.

Third, an ATIO must cover the full AFS, from inputs to primary production through consumer food choice environments. For many decades, producing sufficient healthy food to meet the expanding needs of a growing human population in the face of finite natural resources was perceived as a central task of AFS. This supply side focus naturally led to a heavy emphasis on monitoring inputs and outputs on farms, fisheries and forests and on boosting productivity. Those tasks are indisputably important and necessary. But they are also insufficient.

An ATIO must cover more than just farm-level production for the simple reason that more than 70 percent of the value addition reflected in consumer food expenditures globally occurs post-farmgate (Yi *et al.*, 2021). Moreover, single-minded pursuit of ever-greater efficiency has had predictable, if unintended, consequences, for environmental and human health, resilience to shocks, and working conditions, both within the primary sectors of agriculture, fisheries and forestry, and in downstream processing, manufacturing and distribution (Herrero *et al.*, 2021).

The collection of good and comprehensive data on farm-level production has proved challenging; expanding to cover the full value chain increases that challenge considerably. Coverage will necessarily be sparse initially and expand over time. But one of the biggest contributions an ATIO can make is to expand policymakers' field of vision around AFS transformation to encompass the full value chain, from inputs through primary production – including de-agrarianized (i.e. non-farm) food production (e.g. cellular meat, vertical farming) – processing and packaging, manufacturing, and distribution (including food service), to the food environments in which individuals make dietary choices. A key lesson from recent research on food loss and waste, for example, is that we can only understand and address AFS challenges through such a holistic approach (Cattaneo *et al.*, 2021; Hamilton *et al.*, 2022; Van Zanten *et al.*, 2019).

An ATIO would thus build on and differ from existing sources. Relative to existing STI outlooks from multilateral organizations, an ATIO would focus more tightly on AFS than current OECD, UNESCO or WIPO products do, going into much greater depth on AFS STI and associated impacts. Relative to existing FAO publications and data products, ATIO would also help stimulate and coordinate investment to fill in key data gaps between primary producers and end consumers, while also expanding coverage of policies and institutions central to AFS transformation, and of horizon-scanning and foresight analysis. This would likely be done most effectively in a consortium model, in collaboration with other key stakeholder organizations with demonstrated expertise in one or more relevant domains (section 11). This is a vast task, however, so it will be essential to draw some clear boundaries on the ATIO activity so that it adds value, enhances cooperation and coordination in a crucial space, and offers fit-for-purpose data and analysis.

BOX A THEMES OF OECD, UNESCO, WIPO AND UNCTAD SCIENCE, TECHNOLOGY AND INNOVATION REPORTS

OECD Science Technology and Innovation Outlook

2021 Times of Crisis and Opportunity.

2018 Adapting to technological and societal disruption.

2016 Comparative analysis of new policies and instruments being used to boost the contribution of science and innovation to growth and to global and social challenges.

2014 Overall innovation performance and policy trends.

2012 The driving role that science, technology and innovation are expected to continue to play towards a sustainable and lasting recovery from the economic crisis “megatrends”.

2010 Performance in science and innovation, trends in national STI policies and the design and assessment of innovation policy, including policy interactions and the “policy mix”.

2008 Science and innovation performance; trends in national science, technology and innovation policies; and practices to assess the socio-economic impacts of public research.

2006 The role of intellectual property rights and technology licensing markets in innovation performance, policies to enhance benefits of the globalization of business R&D, human resources for science and technology, and the evaluation of innovation policy.

2004 Role of public/private partnerships in stimulating innovation, determinants of service sector innovation, global challenges related to the supply of human resources for science and technology, and the contributions of multinational enterprises to productivity growth and innovation.

2002 Changing business strategies for R&D, competition and co-operation in the innovation process, changes in the governance of national science systems, strategic use of intellectual property rights in public research institutions, industrial globalization and the international mobility of scientists and engineers.

UNCTAD Technology and Innovation Report

2021 Catching technological waves: Innovation with equity.

2018 Harnessing Frontier Technologies for Sustainable Development.

2015 Fostering Innovation Policies for Industrial Development.

2012 Innovation, Technology and South–South Collaboration.

2011 The important role of renewable energy technologies in responding to the dual challenge of reducing energy poverty while mitigating climate change.

2010 The challenges of improving agricultural performance in Africa and the role of technology and innovation in raising agricultural production and incomes of all farmers, including smallholder farms.

UNESCO Science Report

2021 The race against time for smarter development: transitioning to digital and “green” society.

2015 Towards 2030: an effective growing strategy, innovation and mobility trends.

2010 The current status of science around the world: the growing role of technology in the global economy.

2005 Building knowledge societies: universities, technology personnel and R&D inputs

1998 Science and technology globalization: how science and technology safeguard food and water under demography and environmental stress.

1996 Challenges related to science technology and gender dimension.

1993 Status of global science, science and technology system and cooperation.

WIPO Global Innovation Index

2021 The impact of the COVID-19 pandemic on innovation.

2020 Who Will Finance Innovation?

2019 Creating Healthy Lives — The Future of Medical Innovation.

2018 Energizing the world with innovation (energy innovation).

2017 Innovation Feeding the World (Agriculture).

2016 Winning with Global Innovation (global investment and cooperation).

2015 Effective Innovation Policies for Development

2014 The Human Factor in Innovation (Knowledge-Based Economy).

2013 The Local Dynamics of Innovation.

2012 Stronger Innovation Linkages for Global Growth.

2011 Accelerating Growth and Development (innovation measurement and sustainability).

ITALY
Horses grazing below wind turbines on a hillside at a wind farm in Frosolone.

© FAO/Alessia Pierdomenico

CHAPTER 3
AGRIFOOD SYSTEMS SCIENCE, TECHNOLOGY AND INNOVATION DEVELOPMENT AND DIFFUSION DYNAMICS

Across all sectors, the process of technology development and diffusion follows a standard dynamic pattern. Because an ATIO seeks to inform private and public sector decision-making at all stages of the AFS STI life cycle, it should gather data and analyse across four distinct stages of STI development and diffusion that cumulatively span years, often decades. These stages begin with (i) the AFS STI inputs (e.g. R&D financial investments, human, physical and social capital) that generate (ii) pre-emergent STI – i.e. those under active development but not yet in use outside the community of developers – some subset of which gain traction and become (iii) emergent STI observable in use outside researchers' control, and finally become (iv) mature STI before, in many cases, growing obsolescent.

First, knowledge creation does not occur in a vacuum. Rather, knowledge begets knowledge because innovation is fundamentally combinatorial. Major new inventions and impactful innovations have always come about through the intentional combination of different prior discoveries with the express intent of solving an emergent human need (Usher, 1929; Weitzman, 1998; Arthur, 2009; Feinstein, 2011). Similarly, institutional innovations are essential to reducing transaction costs to exchange and the risks of capital investment and innovation (North, 1991, 2008; Platteau, 1994a, b; Barrett, 1997).

Transformative innovation therefore requires pre-existing knowledge and materials, as well as scientists, engineers, farmers, producers, business and social entrepreneurs, and other AFS actors able to combine and recombine pre-existing ideas and materials, and investment of new resources – R&D funds, laboratories, experimental sites, computers, farmland, etc. – necessary to undertake the work. This phase of early-stage ideation – basic science – and the applied and adaptive research that follows it is also affected by institutions and policies – e.g. intellectual property rights regimes, biosafety protocols, cultural norms around creativity and experimentation, and institutional safeguards for research ethics – that influence the efficiency with which financial and material inputs turn into new, useful discoveries. Together, these financial, human, institutional, and material resources represent the inputs to STI production. STI does not emerge without these essential inputs, which can be found in university laboratories, in the fields of innovative farmers, in entrepreneurs' garages, and in the kitchens of creative chefs. While most accounting of STI inputs focuses on formal research systems embedded in national AFS R&D programmes and the like, the essential human and natural capital for experimentation exists equally in informal spaces. That is, after all, how humans first domesticated wild plants and animals thousands of years ago and have continued to do so quasi-experimentally ever since.

The second stage in STI development and diffusion dynamics is the process of ideation, recombination and refinement enabled by investment in STI inputs. This second stage is the period when basic and applied scientific advances occur, when people – researchers, farmers, producers, policy analysts, entrepreneurs – develop new ideas, materials and methods, test new hypotheses, do fundamental design and prototype construction work, etc., all with the goal of developing a product or process worth introducing and testing in the real world. The scientists, managers and innovators engaged in formal or informal R&D continuously adapt, combine and refine novel STI in the pre-emergent phase before the first public (commercial or non-commercial) releases of the STI occur. Here too, much activity takes place outside of the domain of formal research systems, often unseen until new

STI emerges and begins to propagate organically, because AFS change is social as well as technical.[7]

This is the stage during which horizon-scanning is essential, to identify new STI that could eventually impact AFS before the STI emerges in real world applications. This pre-emergent period is arguably the most difficult phase to monitor because it requires tracking ideas before they turn into new products or processes in actual use. Yet this is also a key stage in which policymakers can exert considerable influence to accelerate (or slow the emergence of) innovations through various institutional and policy accelerators (Herrero *et al*., 2020). Moreover, policymakers must plan for predictable, if unintended (positive or negative) spillover effects of new STI because spillovers are ubiquitous, so it is necessary to explicitly track to pay attention to trade-offs and synergies (Herrero *et al*., 2021).

This second stage commonly takes many years. The lag from STI inputs, like AFS R&D investments, to emergent STI generating measurable impacts at scale takes years, often decades (Chavas *et al*., 1997; Ahmadpoor and Jones, 2017; Alston and Pardey, 2021).[8] Given the urgency of addressing climate, in particular, and the uneven progress towards achieving Agenda 2030, progress must be accelerated, which requires greater end-to-end STI life cycle monitoring and management than has existed previously, especially in AFS.

The third stage is the period of STI emergence, when an innovation moves from its source of origin – often, but not always, research stations, laboratories and academic journals – into the real world, uncontrolled use by agents not involved in developing the STI originally. The initial release of emergent STI from formal research systems involves pilot trials in a limited number of locations carefully chosen to test the concept and to generate initial data to use in adaptive research for further product or process refinement. As novel STI gets released into AFS, the emergent STI is monitored and evaluated. But it may also begin to diffuse or adapt spontaneously among newly exposed populations, feeding learning. This is the crucial period in which new innovations either gain traction and begin to diffuse and scale in use, wither and disappear to archives and libraries, or remain in an extended limbo of technical feasibility without adoption at scale until some change makes them more attractive than they were at initial introduction (Rogers, 1962). The incentives and constraints created by policies, institutions and markets play a major role in determining whether novel STI matures or stalls early in its infancy. Institutions and policies that facilitate the bundling of novel STI with complementary innovations can be especially valuable, as virtually no new STI scales on its own; all require bundling with other innovations (Barrett *et al*., 2022a).

Some emergent STI adapts and diffuses sufficiently that it becomes mature (stage four), i.e. widely adopted and changing less dramatically and frequently as it diffuses further. Because the returns to production or use of a novel STI commonly depend on the scale of diffusion, due in part to network externalities,[9] STI that generate significant gains may require sponsorship to overcome the intrinsic advantages of incumbent STI (Katz and Shapiro, 1986). Ultimately, the use of many mature technologies – even those that become (temporarily) dominant – wanes or even becomes obsolete as newer technologies emerge to displace them or as the AFS evolves and renders the mature STI less effective or desirable (e.g. some disease treatments or horse-drawn transport or tillage).

The resulting diffusion curves typically start slowly before climbing at an increasing rate as people rapidly learn of and experiment with a new technology, then the rate of adoption slows as the STI saturates is application domain, yielding an

7 A good example is the system of rice intensification (SRI). SRI originated with experimentation in smallholder farming communities in Madagascar in the 1980s, diffused after the original developers created a local nongovernmental organization, Association Tefy Saina, to extend the suite of innovative practices to other farmers, and is now practised in more than fifty countries worldwide (Stoop *et al*., 2002; Glover, 2011; Barrett *et al*., 2022b).

8 The estimated lags vary by the discipline of discovery, with more basic sciences like mathematics generating impact with longer lags than more applied ones, such as computer science (Ahmadpoor and Jones, 2017) and private R&D investments generating larger near-term – in the 5 to 15-year window – payoffs, with public R&D delivering bigger longer-term gains at 15 to 25-year horizons (Chavas *et al*., 1997).

9 Network externalities exist when one user's valuation of a good or service depends on how many others use the same (or a compatible) product. Unlike more familiar technological externalities (e.g. pollution) that originate from the supply-side, network externalities stem from demand-side phenomena.

S-shaped contagion pattern. This is seen frequently in studies of the diffusion of a wide array of STI, in AFS and elsewhere in society.

Note that diffusion curves at national or global levels necessarily reflect aggregate patterns and may mask considerable heterogeneity among smaller units of analysis. An STI that may be quite mature in some AFS may be merely emergent, even pre-emergent, in others. Some spatial variation in uptake can arise due to structural conditions that make a given STI more appropriate in some spaces than others, such that steady state uptake will vary considerably. But spatial variation can also vary due to sequenced cross-boundary spillovers (Aghion and Jaravel, 2015; Mason-D'Croz *et al.*, 2019). To the extent data permit disaggregated analysis, ATIO can explore variation in diffusion among different agroecosystem, market or regional contexts.

A key, defining feature of the emergent STI stage is that the innovation is not yet sufficiently widely used that any organization has yet begun to track uptake in a systematic, replicable way and make those data widely available. People and organizations grow increasingly aware of emergent STI but typically struggle to gauge the extent or pace of adoption. Emergence is shrouded in uncertainty.

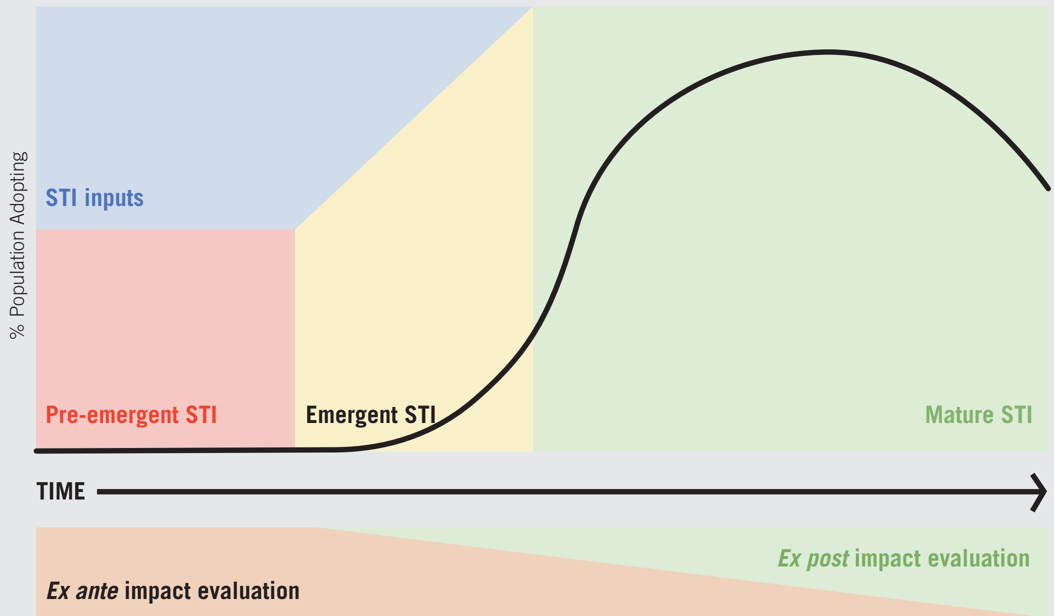
At some point, however, an STI becomes mature, entering a fourth stage in which the innovation has gained sufficient traction and the rate of adaptation has slowed such that someone starts to measure its growing reach routinely. The boundary between emergence (stage three) and maturity (stage four) is necessarily hard to define precisely. Some mature STI do not get measured systematically across countries. But virtually all AFS STI that do get systematically tracked are mature. In some cases, maturity yields to obsolescence. This occurs when a new, superior technology arises to supplant its predecessor(s), as was the case with the use of horses for traction and transport. Obsolescence also arises due to evolutionary pressures, for example, as pathogens, pests and weeds adapt and diminish the effects of previously productive herbicides, pesticides or seed varieties.

Cumulatively, these four stages map to different data needs, as the subsequent sections explain and as Figure 2 depicts. The STI development and diffusion dynamics lead to four distinct data classes – for STI inputs, pre-emergent STI, emergent STI, and mature STI – that are differentially available at present. Data on STI inputs – e.g. public, private, and philanthropic R&D finance, scientific staff and infrastructure, farmer-based experimental platforms (such as FFS and STBs) etc. – exist, but have important deficiencies, as section 5 explains. Mature STI data are relatively more plentiful, but are largely limited to primary production in AFS, with far less comprehensive, reliable, and timely coverage post-farmgate, as section 8 explains. And data on pre-emergent and emergent STI are largely unavailable, each requiring different data collection and processing methods, as sections 6 and 7 explain. Integrating these data sources and related analyses is the central challenge and value added of an ATIO, one that, according to the theory of change outline earlier, should help both unlock investment upstream in AFS STI R&D and stimulate diffusion and adaptation of STI, especially in LMICs.

AFS transformation requires multiple simultaneous transitions. Rarely do STI emerge at the same pace across AFS and value chain stages. The interdependence of STI diffusion in one space on advances in another – e.g. higher-yielding seed varieties can only gain traction if market institutions likewise evolve to absorb increased farm surpluses without commodity prices crashing – puts a premium on AFS governance. Hence the need for an integrative ATIO that looks across AFS – as innovation in one AFS can easily adapt and diffuse to another – and throughout AFS, and that takes a long-term view. The major challenge in this task is data, the topic of the next section.

The stage of STI development also maps to the methods used to try to assess impact. ATIO aims to help foster accelerated AFS transformation to attain multiple goals: efficient and sustainable use of scarce resources, prosperous and equitable livelihoods for producers, workers and enterprise owners throughout the AFS, healthy and safe diets for all persons, and resilience to shocks and stressors. STI must be assessed with reference to

FIGURE 2 **SCIENCE, TECHNOLOGY AND INNOVATION DEVELOPMENT AND DIFFUSION DYNAMICS AND DATA CATEGORIES AND RELATED IMPACT EVALUATION METHODS**



those intended impacts. As shown in the bottom panel of Figure 2, until an STI has emerged from laboratories, experiment stations, farmers' fields and other sources of structured experimentation, all impact assessment is necessarily *ex ante* of uptake, i.e. based on simulation modelling, whether that is expressly numeric or implicit, mental models that feed into qualitative expert assessments. *Ex ante* impact assessment is useful even after STI has emerged, not least of which as a part of foresight exercises to try to understand how impacts might vary across different possible AFS futures (Thornton *et al*., 2018; Wiebe *et al*., 2018; Barrett *et al*., 2022a).

As new STI emerges in actual practice beyond researcher-controlled trials, *ex post* impact assessment begins to play an essential role in rigorous evaluation of the real-world outcomes attributable to a specific (or bundle of) STI. Rigorous *ex post* impact assessment has attracted considerable attention in recent years, both in one-off evaluations undertaken by various organizations and investigators and via broader research programmes, as discussed in section 9. Sampling and measurement error necessarily cast doubt on the generalizability and reliability of even well-done single evaluation studies; replication is needed to build a convincing evidence base. Evidence synthesis of the body of impact assessment evidence, via scoping and systematic reviews, statistical meta-analysis and other methods, can shed light on what reliably works, where, and under what conditions. Integrative impact assessment efforts can generate powerful evidence to inform policymakers about AFS STI, as demonstrated by the Ceres2030 project, for example (Laborde *et al*., 2020), which published a collection of evidence synthesis studies in the *Nature* journals (https://www.nature.com/collections/dhiggjeagd/).

The multiplicity of desired impacts from AFS transformation also necessitates paying explicit attention to trade-offs among different goals. No STI generates favourable impacts in every domain; all involve both positive and negative spillovers on other desirable outcomes, given the closely coupled nature of AFS (Herrero *et al*., 2021). Therefore, explicit trade-off analysis should be embedded in both *ex ante* and *ex post* impact assessment (Kanter *et al*., 2018; Antle and Valdivia, 2021) at all scales from global assessments (Hasegawa *et al*., 2018; van Meijl *et al*., 2018, Rosegrant *et al*., 2017) to national (Sain *et al*., 2017) and local assessments (Valdivia *et al*., 2017). The multiplicity of impacts will also necessitate the inclusion of a wider array of perspectives to understand potential challenges to scaling better, as well as vulnerable populations susceptibility to unintended consequences. This will need to build on participatory foresight approaches that attempt to incorporate a greater range of alternatives and wider uncertainty systematically (Trutnevyte *et al*., 2016; Vervoort *et al*., 2014; Zurek and Henrichs, 2007).

The vision of ATIO as an open access, end-to-end STI life cycle resource for descriptive and impact assessment evidence relevant to AFS globally and nationally holds considerable appeal. But it will also require considerable investment and work, not only for data curation but also for designing novel data collection and proxy indicator construction to fill key gaps in the current AFS STI data landscape.

GABON
Bushmeat DNA is processed at the CIRMF lab complex in Franceville, Gabon. Hundreds of samples are brought into the lab from field researchers and processed as part of the lab's commitment to fighting zoonotic disease.

CHAPTER 4
DATA NEEDS AND APPROACHES

To understand how STIs can impact AFS and communities at large, it is important to map and evaluate the data landscape that houses information and indicators about these technologies and innovations. Data overall, but especially in the context of agrifood technologies and innovations, can be identified across four categories that factor in data accessibility, quality and completeness.

The first category of data is that which is easily accessible, high-quality, complete and standardized. Data sources in this category are considered **structured** data sources with easily quantifiable contents that can be analysed relatively efficiently. Big data, including satellite imagery and remote-sensing data, are increasingly used to support the monitoring of regional or global agriculture systems (Fritz *et al*., 2019).

The second category is still accessible **semi-structured** data, such as that stored in relational databases. Semi-structured data, as the name implies, exhibit some structure but lack uniformity, making analysis – especially statistical hypothesis testing – more difficult than for structured data.

Most data, however, exist as **unstructured** data, such as texts and images. Unstructured data present greater challenges with standardization and analysis because they lack a predefined structure to measure across a set of indicators to build a more comprehensive, consistent dataset. By leveraging data proxies and frameworks for analysis based on expert insight, unstructured datasets can be curated for future analysis.

Finally, the fourth and most challenging data category includes currently **unavailable** data. It is obviously infeasible to derive information when no data are available. There are two different types of unavailable data, however. One type relates to data that could be directly observed and measured but are not. Those are data gaps that could be filled if adequate demand for the data justifies the cost and effort to collect the data.

A different type of unavailable data relates to latent, inherently unobservable – and thus not directly measurable – phenomena. Examples include concepts such as food security, poverty, resilience, or sustainability, for which considerable effort has been made to create feasible proxy indicators with reasonable information content (Barrett, 2010; Barrett *et al*., 2021b). One must be careful not to simply assume that proxy indicators have real signal about the underlying latent concept.[10] All proxy indicators, like all direct measures of observable phenomena, require validation. Many STI that have not yet materialized in tangible, measurable forms fall into this latter type of latent, unavailable data for which one can, in principle at least, generate proxy indicators.

Overlaid with these different types of data are different analytical uses of data, of which there are at least three. **Descriptive analyses** simply report on the present and/or past state of a measure or indicator. Examples of descriptive analyses of AFS STI data include reports on R&D expenditures or on the diffusion of technologies across space and time. Descriptive analyses lay the factual basis for the other types of data analysis. FAOSTAT is a leading example in the sector of a structured dataset (collection of datasets) widely used for (but not only for) descriptive analysis.

10 For an example related to proxy measures for the increasingly popular concept of household-level resilience to shocks and stressors, see Upton *et al.* (forthcoming).

Predictive analyses generate model-based forecasts of future phenomena. Predictive analyses often emerge from statistical or mathematical models, as with more elaborate scenario-based foresight analyses. But predictive analyses can also be qualitative, as when experts try to identify where and when new STI will emerge in everyday use. Predictive analyses are especially important to foresight analysis, which require imagining a range of alternative futures and thinking about their likelihood of occurring, and prospective impacts, all of which arise from predictive models, formal or informal, explicit or implicit.

Finally, **inferential analysis** uses data to try to understand causal patterns. The broader big picture objective of ATIO is to help inform public and private sector policy to accelerate AFS transformation in pursuit of the SDGs and related societal goals. It is therefore necessary to know which STIs cause meaningful improvements in key performance indicators, i.e. which have a large 'effect size' in the language of experimental evaluation. But rigorous causal inference demands high quality data and good research designs. This can be difficult to achieve in observational data from complex, real world AFS, however.

The primary focus of ATIO is descriptive analysis. The primary reason is that it is necessary to know what is and was before it can be predicted what will be or rigorously infer what caused observed phenomena. Good predictive and inferential analysis always starts from reliable structured or semi-structured data and indicators of latent phenomena. An important secondary reason is that, as subsequent sections document, data gaps abound in the AFS STI space, both due to unavailable data and to underinvestment in the public good of collection, processing and curation of structured, semi-structured and unstructured data.

While ATIO's primary data objectives would be to build and curate high quality descriptive evidence, ATIO should be designed to facilitate good predictive and inferential analyses as well. Ideally, ATIO would curate predictive and impact assessments alongside the descriptive evidence, if adequate resources emerge. Box B describes some of the data challenges that are especially acute and salient for ATIO.

Finally, these approaches focus on capturing innovation as it happens, or has recently occurred, as a sociotechnical process. ATIO embraces the opportunities for information from diverse sources as part of the spectrum of innovation, recognizing that where one finds evidence of innovation may not be the same place as where innovation or related technologies originated or ultimately flourish. More qualitative information, such as case studies, interviews and farmer-focused discussion groups are rich sources of data that cannot be ignored as part of the ATIO. The challenge, of course, is integrating such data, which are rarely standardized across countries nor sufficiently broadly available to satisfy the inclusion criteria developed for existing data series. Most likely, qualitative information will enter ATIO through the expert and stakeholder elicitation processes described in section 6.

An outlook must be based on evidence. But the scale and diversity of AFS make it infeasible to have a comprehensive database. Rather, this report maps indicators that present the current state of ATIO while also selecting indicators that could potentially support future ATIOs. Using STI inputs, pre-emergent, emergent, and mature STI stages, this report identifies and evaluates STI trends to understand better their connection to and impact on AFS. In doing this, ATIO looks to pair high-quality data that are regularly updated with a series of relevant indicators that enable continuous monitoring and evaluation across STIs. This combination of data and indicators is useful to identify future trends and current gaps while simultaneously evaluating how progress is being made over time.

STI inputs data (section 5) have been collected by various groups, such as the International Service for National Agricultural Research (ISNAR), Agricultural Science and Technology Indicators (ASTI), International Science & Technology Practice & Policy (InSTePP) etc., using structured and semi-structured data sources on, for example, AFS R&D expenditures or PhD scientists. Some groups, like WIPO's GII, generate indicators for latent concepts such as the policy environment for private sector innovation. Most STI inputs data analysis is descriptive, but some is inferential, as

BOX B DATA CHALLENGES

It is important to highlight a series of data challenges that impact how inclusion criteria are determined and implemented for Agrifood Systems Technologies and Innovations Outlook (ATIO).

Data availability in LMICs. Science, technology and innovation (STI) data from low- and middle-income countries (LMIC) are more difficult to access in a timely manner and there are issues with data quality that makes it more challenging for LMIC-sourced data to be integrated into other datasets. The lack of access to existing data from LMICs makes it difficult to identify agrifood innovations targeting LMICs specifically. Although it might be true that technologies and innovations from non-LMICs can be adopted and used in LMICs, additional efforts must be put into justifying how and why such a technology/innovation would work in a different context. Conversely, LMICs have a harder time accessing data from data-rich countries due to paywalls, data storage issues, and a lack of structures that enable data sharing and interoperability.

Dearth of data on policy environments and the 'missing middle' of agrifood value chains. Systematic, standardized agrifood systems (AFS) data collection has historically focused on farmers, fisherfolk and other primary producers, or on food consumers. Although post-farmgate activities account for more than 70 percent of the value addition in consumer food expenditures globally (Yi *et al.*, 2021), few systematic data series exist to cover this diverse range of impactful food service, manufacturing, processing, retailing, storage, transport and wholesaling activities. Likewise, although international variation in policy environments explains more observed variation in household AFS technology uptake than do household-, agroecosystem- or market-level phenomena (Sheahan and Barrett, 2017), scant comparable cross-national data exist on policies that impact AFS broadly.

Double counting. Another challenge to consider is how often data are double counted in evidence analyses – especially when considering STI data. For example, information about a new AFS STI could be found in an emergent STI data source (i.e. patent data) but could also be uncovered during a pre-emergent structured interview with a sector expert. Trying to merge data may result in double-counting, which adds a greater weight to that STI. While STI data can be categorized in multiple ways, it is important for an ATIO to clearly define how data will be categorized and counted early on.

Lag in impact assessments: When using indicators as proxies for impact assessments, one can run into difficulties measuring the effect of an innovation or technology. Given the emergent nature of innovations or early technologies, identifying and evaluating outcomes or impacts to AFS can take a longer period of time. It is difficult to draw conclusions and provide suggestions from agricultural technology ideas that have not been implemented. There is a lag between the emergence of scientific research and implementation as operational activities (Fritz *et al.*, 2019).

There are several ways to address the aforementioned data challenges. Including data in languages other than English would increase the data available for curation and analysis, with the potential to include data from more LMICs. With the collection of data from more diverse sources, more consistent calibration and data validation protocols need to be set clearly so that errors such as double counting can be resolved or decreased. It is also important to set clear definitions for each term used throughout the data collection and validation process. One key outcome of ATIO, however, will almost surely be identification of important data and evidence gaps, which might help induce efforts to fill those voids.

with estimates of the rates of return to AFS R&D investments (Pardey *et al.*, 2018).

Pre-emergent STI (section 6) data are the most challenging. Typically, there is a need to fill gaps of unavailable data. This usually involves latent variables – e.g. the readiness level of an STI – and unstructured or semi-structured data, much of it inherently non-quantitative. For pre-emergent STI, descriptive analysis is almost inextricably bound up with future thinking – which STIs are likely to emerge, when and where? – and inferential analysis – which STIs exhibit enough promise to cause desirable changes that are expected to emerge from the laboratory and diffuse? Describing pre-emergent AFS STI almost requires the other data analyses in a way that, for example, reporting levels of AFS R&D does not.

In the context of **emerging STI** (section 7), key indicators that are used to identify innovations include: patent indicators, bibliometric indicators, investment indicators and service indicators. More information about these indicators is provided in section 7. Application of structured expert elicitation can facilitate access to and synthesis of knowledge (published and unpublished) of emerging STI, and through *ex ante* assessment of transformative potential, can help to narrow the focus of the ATIO.

Data on **mature STI** (section 8) are the most plentiful, especially as structured data, because monitoring systems exist to gather and release data. National statistical offices, industry groups, and others routinely field surveys and censuses to count things. Some of those things relate to AFS STI, such as quantities of fertilizers applied to fields or the number of advanced machines in use in an industry. But much of the data on mature STI are unavailable or at best semi-structured because although data exist – e.g. in crop varietal improvement approvals registries – they are not systematically reported and standardized across years, crops or countries. But data collection and standardization are costly exercises. Especially in LMICs, many data gaps exist simply because there are insufficient financial, human and other resources to provide this public good.

Across all indicators, it is necessary to pay attention to a series of factors that may impact the overall quality of those indicators. In the context of technologies and innovations, these can include contextual readiness, suitability, acceptability, uptake, impact, timeliness, and manipulability of indicators by interested parties, attempt to validate measures via triangulation, and to assess accuracy/precision. One must also distinguish between merely descriptive indicators and actionable ones (e.g. policy levers, road maps to impacts).

RUSSIAN FEDERATION
Milk processing plant. Employees at work on the production line in a dairy factory in Voronezhsky.

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CHAPTER 5
AGRIFOOD SYSTEMS SCIENCE, TECHNOLOGY AND INNOVATION INPUT INDICATORS

The STI to transform AFS over time does not materialize spontaneously. Much originates informally, from intentional efforts to improve AFS. This was true of the initial domestication of wild animals and plants roughly 10 000 years ago and continues today in widespread innovation by individual, or small groups of, farmers, producers, processors, digital app developers, etc. More formal STI efforts arise from structured investments of R&D funding, combined with essential scientific infrastructure and inputs – credentialled, trained experts with adequately equipped facilities and collections of essential raw materials (e.g. genetic material from genetic advances) – in an R&D ecosystem where institutions and policies foster new experimentation, discovery, adaptation and scaling necessary to identify promising STI for AFS transformation. There may also be considerable learning by doing and adaptation; not all impactful innovation originates in laboratories.[11] While there can be considerable gaps between these STI inputs and the ultimate realization of scaling-up such technologies, the evidence that STI inputs foster faster future AFS TFP (total factor productivity) growth is strong, even if the lag is often more than a decade (Alston and Pardey, 2021). So, it makes sense to track STI inputs as leading indicators of the outlook for AFS STI.

A range of institutions already generate or curate different types of data on AFS STI inputs.[12] A systematic process was followed to establish what data already exist that might prove suitable, to minimize unnecessarily expensive duplication of efforts. Nets were cast widely, brainstorming internally to identify series of which authors were collectively aware, asking colleagues for leads, and conducting web searches, all in a snowball-sampling style approach to identify datasets that might provide useful indicators of AFS STI inputs. Series have been missed, especially ones that are not publicly available. Indeed, filling key gaps will require identifying restricted access data series that otherwise meet ATIO's inclusion criteria.

Data are plentiful. Many candidate datasets and series were identified and ultimately 41 different STI input data series were explored in more depth. The publicly accessible data sources range from UN agencies such as FAO, UNESCO and WIPO, to other multilateral organizations like OECD or the World Bank, to non-profit research organizations like CGIAR and IFPRI, to private foundations (e.g. Ford, Gates, Rockefeller), to multistakeholder platforms like GFAR, Gramene, GRIN-Global and OPENICPSR.

Just because data are abundant, however, does not make all series useful. The challenge is finding fit-for-purpose data that offer adequate current, high-quality measures that are both relevant to the topic and with sufficient country-level coverage globally, especially among LMICs. Six basic criteria for inclusion of an open access data series in a prospective ATIO are:

1. Data are available at country-level to permit internationally disaggregated analysis.
2. There exist adequate recent data, meaning the series includes at least one data point from 2016-present for a larger number of (>50) countries.
3. The data series is inclusive, meaning strong (not necessarily universal) coverage of LMICs.

11 A good, if controversial, example in AFS is the System of Rice Intensification (SRI), which originated from backyard experimentation by a missionary priest (trained as an agronomist) in Madagascar and has now diffused to more than 50 LMICs.

12 The same methods were used to identify and assess data on mature AFS STI (e.g. fertilizers, improved seed varieties), as described in section 8.

4. The data source is reliable, meaning it is grounded in accepted scientific theory and practice, uses peer-reviewed processes, comes from respected/credible organization, etc. – includes no advocacy group or journalistic material.
5. A clear conceptual correspondence exists between the data series and AFS STI inputs.
6. The data source offers a clear, credible, interpretable, sensible definition of the variable.

Note that data that are not currently in the public domain were not considered.

For each series identified, data were compiled to describe the variable, its name and definition, its source, the number of countries for which observations were available, the number of countries for which at least one observation was available from 2016-present, and any other salient information on that specific variable and data source.[13] It was then assessed whether the data series satisfied **all six** of the above inclusion criteria. If so, the series was designated for prioritization for inclusion in ATIO. A second iteration of each assessment was carried out to either confirm, refine, or challenge the original assessment to have double entry confirmations of the data series deemed of satisfactory quality to merit inclusion in ATIO. On the rare occasions that multiple, very similar series were found that satisfied all six criteria, the series already curated by FAO was favoured.

As shown in Table 1, of the 41 different STI input series identified, only 14 series satisfied the basic inclusion criteria.[14] Availability of timely, good quality, inclusive data is a significant constraint. Major gaps exist in the STI inputs data series that are publicly available, especially in covering public and private for-profit R&D funding, and R&D personnel. This finding corresponds with the conclusions from a recent CGIAR Commission on Sustainable Agriculture Intensification (CoSAI) study that "a concerted global effort is needed to build a single open-access source of information with a wider scope than is currently available" (CoSAI, 2021, p.4). Much of that effort has focused thus far on STI inputs, as CoSAI concluded that STI inputs are the most important indicators to track based on a belief that inputs are clearest and can be most easily influenced. More comprehensive, granular and transparent STI input data are needed.

Furthermore, much greater emphasis needs to go into building reliable data on private sector STI inputs. Private sector AFS R&D investments have increased sharply over the past generation, in part due to changes in intellectual property regimes (Clancy and Moschini, 2017; Alston and Pardey, 2021). This is as true in LMICs as in HICs. For example, China's private agricultural R&D spending has overtaken not just its public agricultural R&D spending but also both US public and private agricultural R&D spending (Chai *et al*., 2019). The China case is telling as well in that its private sector R&D concentrates more on post-farmgate value chain stages than does US R&D (Chai *et al*., 2019). Securing data on private sector AFS STI is obviously difficult, perhaps especially in LMICs, but continues to grow in importance.[15] Sources such as AgFunder do a reasonably good job of tracking venture capital investments but systematically miss R&D expenditures by established firms, which almost certainly exceeds the funds flowing into new ventures.

Some of those 14 series that currently satisfy the six inclusion criteria may not be sustainable (e.g. the index of plant varietal protection coverage, which was the product of a time-bound research project). Some otherwise appealing series will no longer be available with the discontinuation of the World Bank's *Doing Business* annual report, on which,

13 Variations on the same underlying variable are treated as a single data series. That is, the current dollar, constant dollar, current local currency values of a measure (e.g. agricultural R&D expenditures) are all treated as variants of a single data series, as are variants of those measures reflecting intensity relative to, for example, agricultural output, population or land size. All spring from a single core measure, the nominal agricultural R&D expenditures in a country in a given year. Since the number of transforms of that variable are numerous, the single root variable is used.

14 Appendix A provides more detail on the measures and indicators that satisfy inclusion criteria, as well as those we reviewed that did not satisfy the inclusion criteria.

15 A telling example comes from a recent report by Dalberg Asia (2021) commissioned by CoSAI. They used data from just four countries (Brazil, China, India, Kenya) to extrapolate to all LMICs and based their private sector estimates on data from just 21 companies, only six of which (Archer Daniels Midland, Bunge, BRF, Nippon Suisan Kaisha, Thai Union, and Tyson) are post-farmgate processors. Moreover, it included no firms in food manufacturing, wholesaling, retailing or food service although many of those consumer-facing firms are leaders in setting product standards related to production processes, including in entirely new products and processes (e.g. Walmart's recent investment in Plenty, a vertical farming startup).

TABLE 1 DATA STOCKTAKING ACROSS VARIOUS AGRIFOOD SYSTEMS SCIENCE, TECHNOLOGY AND INNOVATION INPUTS
(indicators/series/number of prioritized)

R&D financing	**Relevant indicator (data source)**
Public (11/4/1)	GERD - Performed by government - agriculture and veterinary sciences (UNESCO)
Philanthropic (4,4,0)	
Private (2,2,2)	GERD - Performed by private non-profit agricultural sciences (UNESCO) Domestic credit to private sector (% of GDP) (World Bank)
Higher Education (2,2,1)	GERD - Performed by higher education agriculture sciences (UNESCO)
R&D personnel	
PhD scientists (2/2/0)	
Extension Officers	
Technicians & equivalent staff (4/2/0)	
STI policy environment	
IP regimes (7/3/5)	Ratification of UPOC conventions (OPENICPSR) Farmers' exception (OPENICPSR) Breeders' exception (OPENICPSR) Protection length (OPENICPSR) Patent scope (OPENICPSR)
Regulatory capacity (1/1/1)	Regulatory Quality Index (WIPO Global Innovation Index)
Start-up environment(4/3/1)	Enabling the Business of Agriculture (World Bank)
R&D physical inputs	
High tech imports (1/1/1)	High technology imports (WIPO Global Innovation Index)
Scientific Publicatinos (1/1/1)	Number of scientific publications on frontier technologies (SCOPUS)
Genetic collections (2/2/1)	Number of accession per country (Genesys)

Legend

(green)	Includes relevant indicator(s)
(yellow)	Includes no relevant indicator(s)
(red)	Search yielded no result

for example, WIPO's Global Innovation Index has historically depended heavily for data series. Thus the 14 currently available input series identified are not only thin but also somewhat fragile as a foundation for assessing the current/recent state of inputs into the production of AFS STI at country level. Because STI inputs represent key leading indicators of future STI stocks and their impacts on AFS transformation, any commitment to undertake an ATIO must involve a commensurate commitment to work towards better, more sustainable coverage of key STI inputs indicators.

Building out data coverage does not need to start from scratch. Data series exist that, in principle, could fill those gaps, if suitable arrangements can be made for reliable, ongoing access to make them fit for ATIO purposes. For example, the Agricultural Science and Technology Indicators (ASTI) programme - hosted for many years by IFPRI – has painstakingly generated cross-nationally comparable, detailed data on agricultural R&D in LMICs. Presently, this is the most comprehensive database on LMICs, although even its coverage – and especially its recency – fail to satisfy the inclusion criteria set for ATIO data. The University of Minnesota's International Science & Technology Practice & Policy (InSTePP) has built an impressive collection of data on public, private and philanthropic agricultural R&D investment and spending, on patent counts and patent family data concerning genetic and genomic innovations in the life sciences, plant varietal rights and crop varietal innovations.[16] InSTePP's data include and build on ASTI data. A close collaboration with ASTI would provide a means for ATIO to work closely with countries and other partners (e.g. InSTePP) to expand and more regularly update the geographic and sectoral coverage of essential, high quality STI inputs data.

It is important to recognize, moreover, that even the best current datasets, like those of ASTI or InSTePP, do not currently satisfy ATIO's inclusion criteria – they have insufficient coverage and currency, and/or are not open access – and focus heavily on the upstream, primary production component of AFS. Gaps in the downstream segments, in food manufacturing, processing, retailing, and food service, and inputs into modifying the food environments that influence consumer dietary choices, are especially large and challenging to overcome.

Data on patents could be included in STI inputs because new discoveries publicly revealed in patent filings become an important input to new AFS STI discovery. That is intrinsic to the combinatorial nature of innovation (Arthur, 2009). Patent data are discussed extensively in sections 6 and 7 as a key source of information to use to identify and track pre-emergent and emergent STI.

But patent data are a complex STI input indicator, and thus excluded, for multiple reasons. The most fundamental reason is that processed global patent datasets do not exist, especially not filtered for direct relevance to AFS STI. Many governments do not make patent data publicly available. Single country patent datasets exist and can be a valuable data source on pre-emergent and emergent STI, as discussed in sections 6 and 7. Thus patent data are an incomplete and noisy STI input indicator at present.

One problem is that inventors commonly file for a patent on the same invention in multiple jurisdictions. Thus, there will be considerable replication of the same discovery across different country-specific patent datasets. And such duplication is not always easily detectable due to differences in patent filing requirements across jurisdictions.

A second problem is that many relevant STI discoveries are never patented. Depending on the nature of the STI and the industry, firms often decide to pursue a trade secrets strategy to maintain competitive advantage in that STI rather than disclose their discovery publicly in a patent filing in the hope of securing a temporary legal monopoly control over the patented discovery. The resulting gaps in STI coverage in patent data are highly non-random and may thereby introduce important biases.

Third, most patents are never commercialized and thus effectively worthless, either reflecting a novel discovery that did not ultimately prove useful, or that was useful mainly in impeding progress by competitors or in extracting value from others' discoveries (Lerner, 1995; Shapiro, 2001). Patent data can thus have a high noise-to-signal ratio for ATIO purposes. Hence the "patent-puzzle" – increases in patenting seem largely uncorrelated with increased innovative activity or total factor productivity growth, perhaps even negatively associated with such outcomes (Boldrin and Levine, 2013). We therefore favour treating patent data as a data source for studying emergent and pre-emergent STI, as discussed in sections 6 and 7.

16 See Pardey *et al.* (2016a) for documentation on R&D spending, which currently covers public spending by 158 countries, typically at annual frequency through 2015, private R&D spending data from many countries (including major ones like China and the USA), patent, plant varietal protection and varietal adoption datasets, as well as estimates of rates of return to R&D investments, all of which are updated regularly (Pardey personal correspondence). Pardey *et al.* (2016b, 2018), Chai *et al.* (2019), Dehmer *et al.* (2019), and Graff and Pardey (2020) offer good examples for analyses based on these datasets.

UNITED REPUBLIC OF TANZANIA
A man fixes a traditional fishing boat at the shore of Lake Tanganyika in Kigoma. Lake Tanganyika is the second oldest and largest freshwater lake in the world and is a principal producer of sardine, sprat and perch.

CHAPTER 6
PRE-EMERGENT SCIENCE, TECHNOLOGY AND INNOVATION INDICATORS

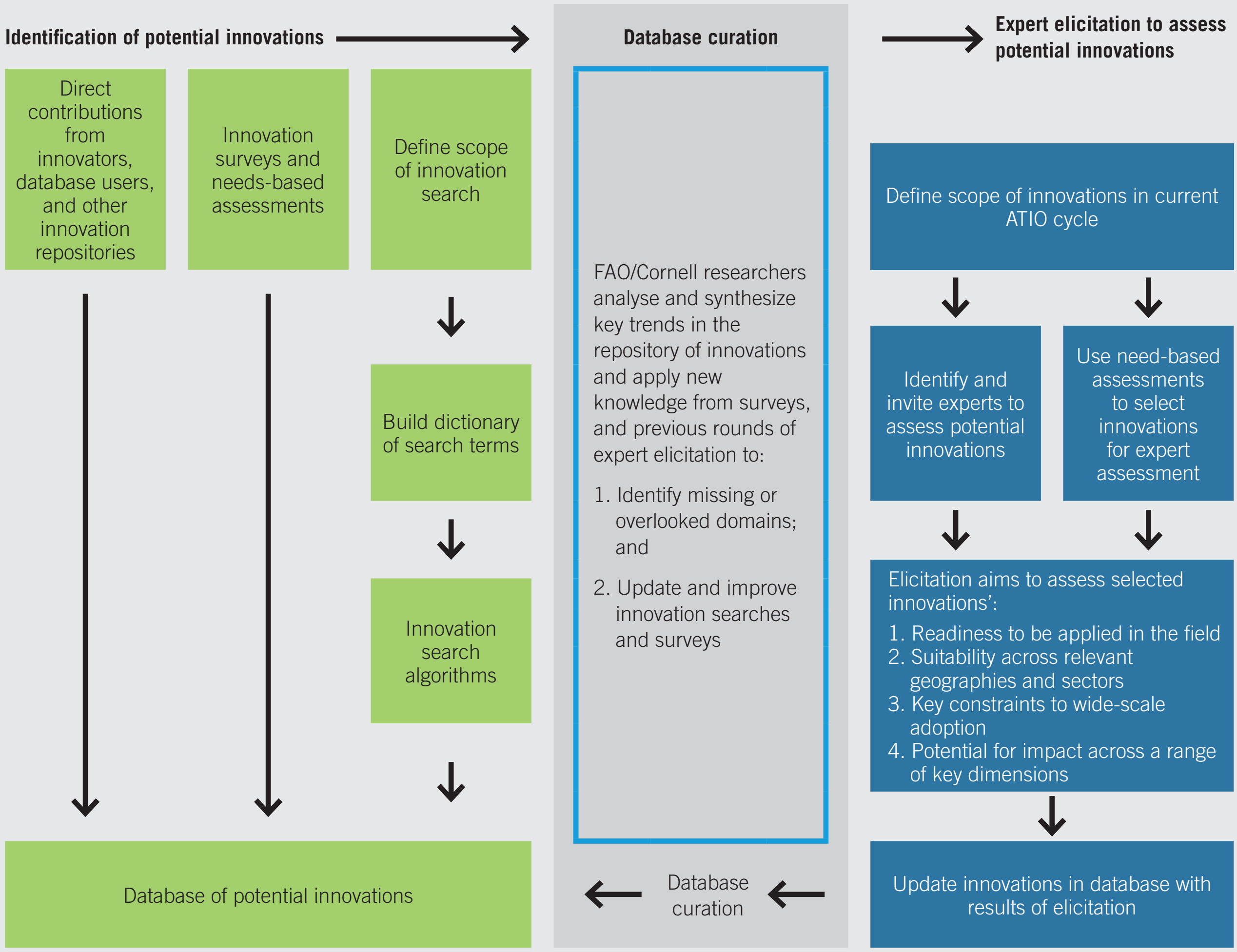
The history of *ex ante* assessment of disruptive technologies is mixed, with substantial criticism of the poor predictive capability of the disruptive technology paradigm (Danneels, 2004; Ganguly *et al*., 2010; King and Baatartogtokh, 2015; Markides, 2006; Paap and Katz, 2004; Yu and Hang, 2010). The ability to predict institutional change and innovation is equally challenged, as these are the outcomes of complex social processes that mobilize institutional entrepreneurs and social stakeholders at varying levels to implement evolutionary changes within existing institutions (e.g. creation of new regulations) to more revolutionary innovations like the creation of novel institutions (Hargrave and van de Ven, 2006). These innovations are often in response to changes in society, which may come from technological innovations, but which can also come from heightened awareness and changes in shared societal values. The difficulty in predicting the future is well recognized and is particularly difficult when considering inherently destabilizing activities like innovation, which offers the possibility of paradigm shifts, the creation of new markets and altering historical links between humans and human activity (e.g. finding value in previously worthless materials).

Given the poor predictive models that currently exist, and the lack of substantial published documentation for pre-emergent technologies, many approaches have looked to assess pre-emergent technologies using expert elicitation, where the pool of experts is not restricted to technical subject matter experts (e.g. research scientists) but may include context experts (e.g. community leaders, farmers, indigenous leaders), or others. Expert elicitation approaches apply futures thinking, which attempts to explore conditional projections based on transparent and explicit assumptions that can be assessed for their plausibility (Bell, 1996). Structured expert elicitation can also help to synthesize available knowledge, published and unpublished (Knol *et al*., 2010), and when well-designed reduce the uncertainty of language to ensure experts answer questions in the same way, clearly indicating assumptions underlying their assessments (Hemming *et al*., 2017; Bojke *et al*., 2021), and increase the quality, transparency and reproducibility of derived knowledge (Knol *et al*., 2010).

To more systematically assess pre-emergent innovations and their potential to transform AFS, an iterative data collection and expert elicitation model is proposed, which will try to identify potential innovations, and through expert inputs try to select and assess highly relevant and potentially transformative innovations in greater detail. Not all types of innovation will be equally represented in literature and online sources, presenting challenges to identifying a broad range of pre-emergent innovations. As such, the ATIO identification process will require a blend of search methods that include conventional and advanced searching techniques (e.g. Natural Language Processing (NLP)) along with accepting direct contributions from innovators and innovation repositories, drawing lessons from citizen science and crowdsourcing of innovative ideas, as well as innovation and AFS needs-based assessment surveys to help identify key problem areas in search of solutions. This approach can be applied for identifying technologies, as was done in Herrero *et al*. (2020, 2021) and the Innovative Food Systems Solutions (IFSS) portal, as well as institutional and policy innovations.

Incorporating need assessments with experts can help to identify and prioritize key challenges facing AFS, recognizing that social, institutional, and policy innovations have historically emerged

FIGURE 3 ITERATIVE IDENTIFICATION AND ASSESSMENT OF PRE-EMERGENT INNOVATIONS APPLYING MIXED DATA COLLECTION METHODS AND EXPERT ELICITATION



in response to identified societal problems and shifts in societal values. Furthermore, these elicitations can complement suitability and readiness indicators to get a sense of the preparedness of societies and institutions to implement potential changes and reforms to address needs (Selinske *et al.*, 2020). The pre-emergent space is one that is constantly evolving, and it is not plausible to capture all potential STI. Nevertheless, if these activities are done on a continuous and iterative basis, where engagement with experts and the wider public can feed back into the identification process through updating of searching algorithms (expanding or narrowing search parameters), over time this process should give a sense of the key STIs that are in the process of emerging on to the scene. Figure 3 highlights some, but not all, of the various data collection methods that could be used to identify pre-emergent innovations, and the links to experts and stakeholders that should inform new iterations of identification and assessment.

In the assessment of select innovations by experts, it will be necessary to disentangle several key conditionalities. The invention of technologies, cultural norms and practices, and novel policy and regulatory environments is only part of the story of innovation, and to assess potential innovations better it is necessary to gauge the maturity of the

BOX C ASSESSING TECHNOLOGICAL MATURITY AND READINESS

Various models have been developed to assess the maturity of technologies better and their potential of being adopted and diffused. On the technology side, The National Aeronautics and Space Administration (NASA) (1991) developed the Technology Readiness Levels (TRLs) to identify and describe different technologies consistently at varying levels of maturity, ranging from the reporting of basic research (TRL1) to proven implementation (TRL9).

This scale envisions a linear technology development process and facilitates forecasting of technological development through the assessment of how far along these development pathways technologies currently are. These levels have been used in expert panels to develop short- and mid-term project timelines and prioritize investments to push forward key but still not ready technologies.

NASA's 9-stage Technology Readiness Levels

Basic research	**TRL1: Basic principles observed and reported**
Researching feasibility	**TRL2**: Formulated technology concept and/or application
	TRL3: Demonstrated proof-of-concept
Technology development	**TRL4**: Validated in lab setting
Technology demonstration	**TRL5**: Validated in relevant environments
	TRL6: Partial prototype(s) demonstration in relevant environment
System development	**TRL7**: Full system prototype demonstration in relevant environment
System implementation	**TRL8**: System completed through test and demonstration
	TRL9: Technology implementation and deployment

Determining the level of readiness of a particular technology can be achieved through scoring by various researchers or through expert elicitation processes to assess and rank the readiness of a portfolio of technologies and innovations. Further information on the readiness of various technologies can also be gained from reviewing databases on venture capital investments, which can distinguish stages of development (discussed in greater detail below).

Sources: NASA (1991) and Héder (2017)

innovation (i.e. is it ready to be applied?), the suitability of the innovation to specific contexts (i.e. is it applicable and scalable?), and the potential of the innovation if adopted at scale to disrupt and transform systems. This requires considering key constraints and the enabling environments that facilitate or challenge the adoption of potential innovations, as well as recognizing the combinatory nature of innovation adoption and identifying essential complimentary innovations, be they technological, social, or policy-based, that will be needed to scale up adoption. The expert elicitation on pre-emergent innovations can apply and expand on existing indices and typologies like NASA's Technology Readiness Levels (see Box C), the Technology Readiness Index (see Box D), or the UNCTAD country frontier technology readiness index (UNCTAD, 2021).

BOX D ASSESSING THE POTENTIAL FOR ADOPTION

The *ex ante* assessment of the potential for adoption needs to consider the many motivating and inhibiting factors that individuals respond to when deciding to adopt a new approach. Recognizing this, Parasuraman (2000) proposed a Technology Readiness Index (TRI) that quantifies the propensity of individuals to embrace a novel technology, considering a range of individual characteristics and factors that are suggestive of the willingness to adopt novel technologies (Blut and Wang, 2020). This index is quantified through a range of questions using a 5-point Likert scale across four main dimensions (technological optimism, innovativeness, discomfort and insecurity), as shown in Figure 4.

FIGURE 4 DIMENSIONS OF THE TECHNOLOGY READINESS INDEX

TECHNOLOGICAL OPTIMISM
To what extent do individuals have a positive view of technology and believe it will improve their quality of life

INNOVATIVENESS
To what extent do individuals have a tendency to be a technology pioneer

TECHNOLOGICAL DISCOMFORT
To what extent do individuals feel disempowered or overwhelmed by technology

INSECURITY
To what extent are individuals skeptical of technologies delivering what they promise

Source: Parasuraman (2000)

While the TRI focuses primarily on the individual, other factors, including the enabling environment, are essential for considering how systematically a novel technology, practice, or norm can be adopted and diffused. Like the TRLs, the TRI index can be estimated through expert elicitation, but could also be targeted to wider audiences through crowdsourcing. The TRI should be expanded to consider the sociocultural, economic and political influences that constrain individual choices like the Afshin *et al.* (2014) model of multilayered influences on dietary choices.

Building on the approach taken in Herrero *et al*. (2020, 2021), ATIO can expand the search parameters of relevant AFS STI to ensure the ATIO database of potential innovations includes not only technological innovations, but also important changes in sociocultural norms and practices, policy and regulatory innovation, organizational innovation, as well as underutilized and ignored knowledge from indigenous sources, small-scale producers, and more broadly from informal AFS entrepreneurs. Further, ATIO can more systematically incorporate best practices in structured expert elicitation, and more explicitly ask experts to assess the previously described conditionalities to assess more rigorously selected STI. To this end, an expert elicitation that attempts to understand four key issues is proposed.

1. Determine the maturity of a potential innovation to be applied in the real world to solve a problem in a specific time horizon (e.g. next five years).
2. Assess the suitability of this innovation to be adopted in a specific context and time horizon, based not only on innovation-specific characteristics, but also on individual and sociocultural factors.
3. Assess the scalability of the innovation in specific contexts and time horizons, recognizing key constraints and needed complimentary changes (e.g. policy, cultural, technological) for adoption at scale.
4. Assess the transformative capacity of potential innovations if adopted at scale, considering potential positive and negative outcomes from their deployment, while trying to control for Amara's Law.[17]

The challenges of expert elicitation are not only in the structural design, but also in identifying and selecting a sufficiently large and diverse pool of experts to ensure engagement with a broad range of perspectives and relevant expertise. A sustainable and continuous series of expert elicitations to inform the ATIO presents further challenges to maintain engagement from experts over an extended period instead of being targeted for a one-off elicitation.

17 Coined by R. Amara, who recognized that there is a tendency to overestimate (hype) the potential of innovations in the short run, while underestimating their impact in the long run.

The remainder of this section will discuss further potential resources and sources of data for developing and extending an inventory of pre-emergent innovations, before discussing the challenges and approaches of building a structured expert elicitation process to assess pre-emergent innovations.

6.1 BUILDING AN INVENTORY OF POTENTIAL INNOVATIONS

The nature of emerging innovations means there may be minimal published scholarly work, and available grey literature may be vague due to lack of concrete applications or to protect nascent intellectual property. Nevertheless, an attempt can be made to catalogue pre-emergent agrifood innovations systematically by compiling an extensive and broad source of potential innovations.

Approaches that have tried to catalogue promising technologies can be built on, including compiling lists of agrifood start-ups that are likely to apply novel technologies and approaches, and collecting information about innovations they are putting into practice. In addition to accessing start-up databases, these lists can be complemented by pulling information about funding sources for agrifood start-ups (See Appendix B for examples of potential sources of information on agrifood start-ups and their funding sources).

Similarly, the policy innovation landscape can be explored by assessing the outputs (e.g. white papers) of influential policy think tanks (e.g. Brookings Institute, Chatham House, FANRPAN), academic institutions and development banks for potential policy and institutional innovations.

It may be more challenging to find sources for underutilized and often ignored sources of innovation, which may have a more limited footprint in published literature (grey and peer reviewed). This may require additional efforts to actively collect such information using targeted surveys and rapid open calls, where experts from any field are allowed to submit a short online form which asks them to identify promising STIs in their sector. The open call offers experts a low-commitment opportunity to participate in the ATIO. Crowdsourcing and citizen-science approaches can also be explored to try to identify a broader range of STIs. All these approaches can help not only to identify key STIs but can also inform search algorithms with unique descriptive words to be used as keywords in natural language processing (NLP) systems. Another potential resource for information on underserved and less represented entrepreneurs could be platforms that promote equity crowdfunding (Box E).

6.2 DEFINING RELEVANT EXPERTISE

The goal of expert elicitation processes is to engage with difficult to access knowledge and expertise across a wide range of perspectives to help better inform our understanding of highly uncertain but important issues. Who takes part in the elicitation will significantly affect the outcomes, as well as acceptance of conclusions of the elicitation by the broader public (Knol *et al*., 2010). Therefore, it is essential to select a pool of experts representing a broad but relevant range of perspectives and knowledge. Furthermore, this pool of experts will need to vary by ATIO iteration to ensure that the scope of knowledge represented by the expert panels reflects the main areas being explored in the relevant ATIO iteration. Given the many potential spillovers of wide-scale AFS transformation, it is important that perspectives beyond the traditional technological and productivity-focused perspective are included to consider implications on the environment, livelihoods, equity, justice, consumption patterns, diets, and health and nutrition outcomes.

Following Knol *et al*. (2010), several main types of expert can be considered that will be needed in expert assessments of pre-emergent innovations:

1. Subject-matter/technology experts who are critical for assessing technology-specific questions, in particular the maturity of the innovation, and the required inputs and intended outcomes of adoption.
2. Generalists who have relevant discipline knowledge and an understanding of the broader context of the development, adoption, and diffusion of innovations. These experts are critical in highlighting challenges to scalability and to identify key constraints to adoption at scale and for specific contexts.
3. Practitioners in the field (e.g. farmers, producers, food processors, traders) who have on-the-ground expertise critical for assessing potential challenges to adoption at scale and can highlight local sources of innovation that might otherwise be missed. Divergent and futures thinkers who are familiar with thinking of and imagining the unintended consequences of innovations and societal change. These experts are essential to raising questions and concerns of potential unintended consequences of adoption, as well as recognizing important non-linearities in the adoption of innovations at scale.
4. Experts in expert elicitation. These experts are important to help organize and synthesize the outputs of expert elicitation.

While in the past, expert elicitations have often focused on selecting technical and academic professionals (e.g. having an affiliation with a relevant research, government, or technological institution), the transformations that these innovations may spur could be society-wide, and as such it is important to have a broad definition of expertise to increase the likelihood of having as many relevant perspectives as possible.
That substantial knowledge of pre-emergent innovations may not be readily found in published and academic sources further suggests the need to have a broader definition of expertise to also include practitioners in the field (e.g. primary producers, food processors, commodity traders), businesses, government, civil society, as well as experts familiar with health and nutrition, while ensuring geographic, cultural and gender diversity.

BOX E CROWDFUNDING IN THE GLOBAL SOUTH

Early-stage entrepreneurs are primarily self-funded or supported by family and friends (Spiegel *et al.*, 2016). These types of arrangement can often be informal, making it difficult to get a full sense of seed funding sources for agrifood systems (AFS). Still, recent advances in crowdfunding provide novel sources of information on funding sources to start-ups. These platforms assist with linking entrepreneurs and investors, helping build brand awareness, and linking start-ups with potential clients.

The development of the equity crowdfunding model is particularly relevant to Agrifood Systems Technologies and Innovations Outlook (ATIO), which looks to increase the transparency of investments and donations, as well as improve access to funding, including to marginalized groups that have historically had limited access to financing and entrepreneurial support.

The expansion of crowdfunding platforms has been impressive, with the development of a range of international, regional, and national crowdfunding platforms. Furthermore, there has been the development of more specialized crowdfunding platforms that target start-ups at specific stages of development (i.e. early-stage investment), or within specific sectors of the economy such as agrifood start-ups. Regionally focused crowdfunding platforms have also emerged with a range of platforms in Africa, Asia, and Latin America, some of which operate primarily at the national level, and others across various countries in the region. While there is substantial variety across crowdfunding platforms, there is an underlying theme of trying to broaden access to funding to previously underserved populations.

The following is a sample of some of the various crowdfunding platforms that could be valuable sources of information on agrifood entrepreneurial activity.

Selection of potentially relevant global crowdfunding platforms

General investment	Early-stage platforms	Agrifood focused
Kickstarter	**Crowdcube**	**Foodhack**
Indiegogo	**Seedrs**	**Vegan Launch**
Crowdfunder	**Ourcrowd**	**Sustainable Food Ventures**
Wefunder	**Fundify**	
Angellist Venture	**Funding Societies**	
Kiva		

Selection of potentially relevant regional crowdfunding platforms

Africa	Asia	Latin America
Farmcrowdy (Nigeria)	**Oporajoy** (Bangladesh)	**PlayBusiness** (Mexico)
Sokaab (Somali regions)	**SeedOut** (Pakistan)	**Kickante** (Brazil)
Fundkiss Technologies Limited (Mauritius)	**Wadiz** (Republic of Korea)	**GreenCrowds** (Ecuador)
Backabuddy (South Africa)	**Sinwattana** (Thailand)	**Patrociner** (Peru)
M-Changa (Kenya, South Africa)	**LetsVenture** (India)	**Broota** (Chile)
Zidicircle (Ethiopia, Kenya, Ghana)	**Tanifund** (Indonesia)	**Idea.me** (Argentina, Brazil, Chile, Colombia, Mexico, Uruguay, United States of America)

6.3 IDENTIFYING AND SELECTING POTENTIAL EXPERTS

The number of experts needed should be determined by the level of uncertainty of the questions being asked of the experts and recognizing facilitation challenges of managing large panels of experts.

To improve the ATIO expert elicitation process further, multiple parallel elicitations should be run. This recognizes that the scope of AFS STI is large and that it is impractical to capture expert knowledge in a single panel. It also allows for more divergence in topics and questions that can be simultaneously explored. There are several key advantages of expert panels. Once experts are divided into panels, they can be offered more targeted calibration questions to improve the weighting of experts' answers (Cooke's Method). Panel surveys can also contain more targeted questions, which will increase the accuracy of answers and allow for more insightful answers. In addition, all panel surveys can include more general questions that are asked to every panel to allow for cross-comparison of all experts involved in the study (Aspinall *et al*., 2016). Further, running multiple panels in parallel can help to reduce the individual burden on expert participants, increasing the likelihood of their continued participation.

Given the high level of uncertainty of assessing pre-emergent innovations, where opinions may vary widely among experts, ATIO expert panels will likely need to be on the larger side, 15–20 expert participants per panel (Aspinall, 2010). However, the selection of these experts should be done with care to ensure that they are contributing unique perspectives from throughout AFS, because adding additional experts with similar views and perspectives has diminishing value and may falsely suggest consensus.

Traditionally, experts have been identified through a range of common practices, including their demonstrated knowledge and experience in the field, recognition by peers and the wider public, and contributions to research outputs (Bojke *et al*., 2021). There are indicators that could be used to simplify the process of identifying experts and cut down on time spent identifying experts. Some of the commonly used indicators for defining an expert, including age, years of experience in their field, scope of expertise (experts with broad or narrow ranges of specialization), number of publications, and experience in particular fields of research or industry (Antonelli *et al*., 2019). Though these basic indicators may be more a signal of prestige than true expertise (Burgman *et al*., 2011), so, ultimately, the final threshold for selection should be that experts are capable of understanding and answering questions in the elicitation. This final step can be achieved in an inception meeting where the selected experts are given the opportunity to learn the design and purpose of the elicitation and ask clarifying questions before committing to participate in the elicitation (Hemming *et al*., 2017).

To improve the final selection of experts further, researchers should attempt to diversify the pool of experts as much as possible. "Diversity should be reflected by variation in age, gender, cultural background, life experience, education and specialization. These are proxies for cognitive diversity" (Page, 2008, as cited in Hemming *et al*., 2017). Given the need to extend the identification and selection of experts beyond traditional experts, it will be necessary to compliment traditional expert identification methods with explicit efforts to include perspectives on AFS innovation from non-traditional and underrepresented perspectives (e.g. small-scale producers, Indigenous Peoples).

One potential source of experts are speakers and participants from the many agrifood summits and conferences around the world. Due to COVID-19, these summits are virtual more than ever, which, at times, can allow for more people to participate. The international agrifood conference scene varies by scale, intention, focus and association. To establish a broad cross-section of conferences, this initial search began with any conferences relating to AFS innovation, technology, investment,

TABLE 2 SUMMARY OF RAPID STOCKTAKING OF CONFERENCES ON AGRIFOOD INNOVATIONS, AND POTENTIAL PARTICIPATING EXPERTS

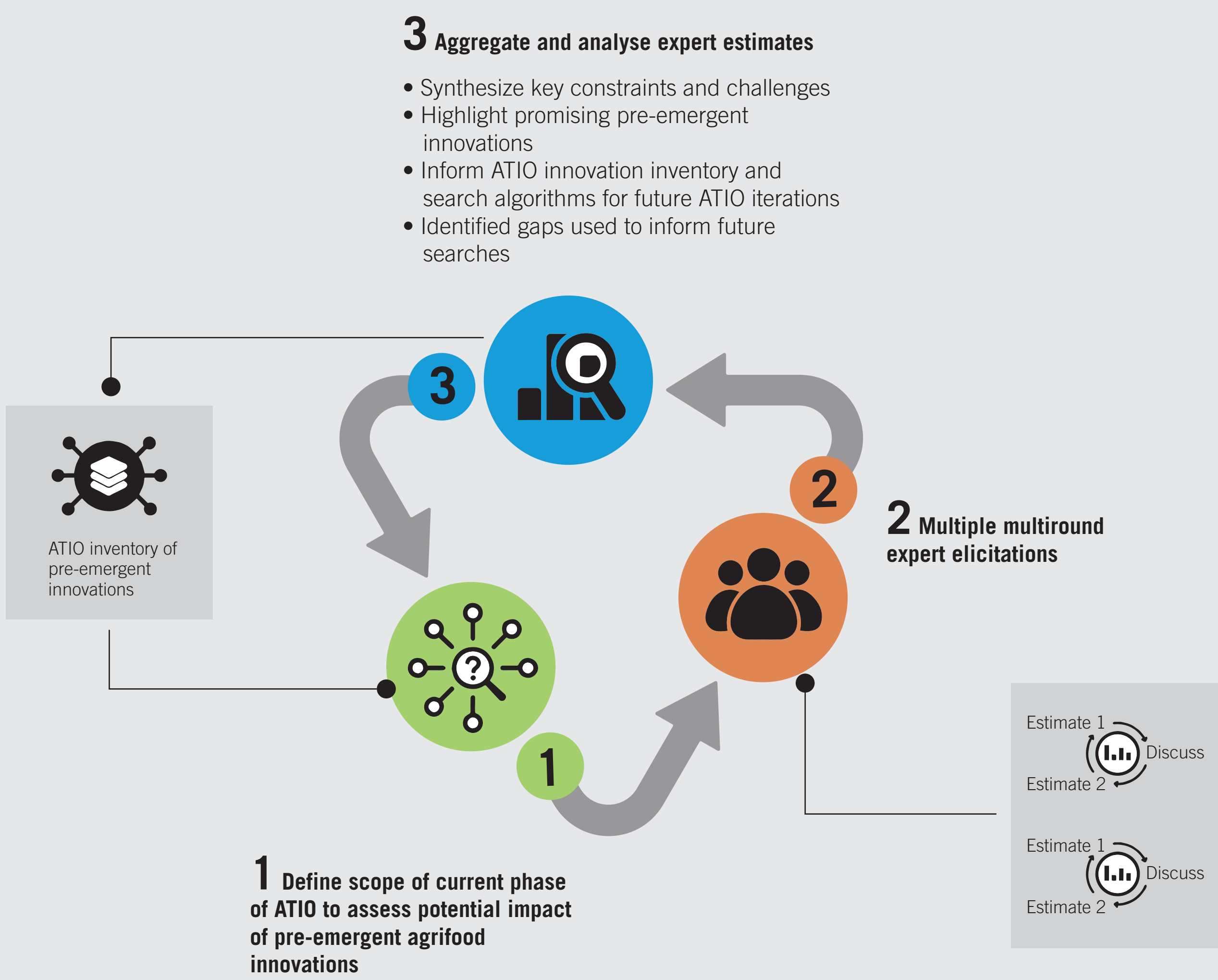
Type of conference	Academic	Industry	Public policy	Venture capital
Types of issue being considered	Climate adaptation, Circular economy, Food waste, Biodiversity, Healthy diets	Alternative proteins, Digitization, Biological crop protection, Supply chain, Circular design	Scaling/Mechanizing smallholder farms, Decarbonization, Resilience, Food system transformation, Climate adaptation/mitigation, Healthy diets	Alternative proteins, Grocery store innovations, Supply chain, Digitization
Innovations spotlighted	Global forecast System, Focus on digital and data solutions, Index-based insurance, Farming data, Governance/Ownership models	Remote crop sensing, AI, Blockchain, Big Data, Plant-based proteins, Robotics	Organic pest management, Circular composting, Open data platforms, Advancements in hydroponics	Hydroponics, Plant-based meat, Alternative dairy, Functional foods, Robotics, Data & analytics, Alternative plant inputs
Whose issues are being considered?	Global, Low income, Middle Income	High income	Global, Low income, Middle income	High income
Value in sourcing experts within this category	Information on relevant research	Information on emerging innovations with an emphasis on scale, production, and existing market	Information on implementation potential, existing models, Previous successful interventions, Status of agrifood systems	Information on new innovations (what is being funded and what is not), Production and market value
Potential experts to target	Speakers, Panellists	Exhibitors, Speakers, Panellists, Advisory boards	Speakers, Panellists, Advisory boards	Speakers, Panellists, Advisory boards

or transformation. After a rapid stocktaking of recent conferences, four general categories were identified: Academic, Industry, Public Policy and Venture Capital. This categorization is not meant to be exhaustive but is helpful in highlighting that different types of conference have different aims, which can facilitate identifying experts with different backgrounds, as participants in these different conferences are likely to be familiar in different areas of the broader innovation landscape. For example, investors may have a better understanding of broader market conditions and financing constraints, whereas industry experts may have more detailed understanding of technological readiness and product features, and public policy experts are more likely to be cognizant of unintended consequences and raise questions about equity and justice. Table 2 summarizes some of the main characteristics of these various categories of conferences.

6.4 STRUCTURED EXPERT ELICITATION FOR ATIO

The expert elicitation process for ATIO must be designed and executed to be sustainable over the long run for both the participating experts, and researchers involved in collecting and aggregating information. To this end, a sustainable process is defined as one that can be performed frequently, recognizes and minimizes the time commitment necessary for both participants and researchers, prevents attrition due to participant burnout, while still producing reliable and valid data. To achieve this will require the development of an expert elicitation research data platform, which facilitates the delivery of surveys to experts, and then collecting, compiling and aggregating expert estimations in easy to access and understand formats to inform expert discussions, and later

FIGURE 5 **A PROPOSED WORKFLOW FOR ASSESSING PRE-EMERGENT INNOVATIONS**



facilitate the ATIO's analysis and aggregation of results.

There is no consensus standard for an expert elicitation model, but the IDEA protocol is becoming a recognized collection of flexible protocols for an elicitation process that improve the functionality and user experience of elicitations. The protocols synthesize best practices from a range of Delphi and Expert Elicitation methods (Hemming *et al*., 2017; see Appendix C for more details in expert elicitation approaches) into a four key steps:

1. (**I**)nvestigate – All experts individually answer questions and provide justifications.
2. (**D**)iscuss – Experts discuss anonymized results from the first round of answers, offered opportunity raise questions and share relevant information.
3. (**E**)stimate – All experts individual answer questions again, revising and updating estimates, if necessary, based on insights from the discussion stage.
4. (**A**)ggregate – Aggregate the individual results to summarize the expert responses.

ATIO, following the IDEA protocol and building on traditional Delphi methods, would implement multiround surveys where experts review and discuss the aggregated results of previous rounds of expert answers, and given the opportunity to adjust and update their own estimates based on sharing of evidence among experts and resolving questions of linguistic ambiguity (Hemming *et al*., 2017). Traditional Delphi approaches have used these stages to foster consensus amongst experts (Cole, Donohoe and Stellefson, 2013), but consensus is not a requirement for the ATIO expert elicitation because there may be more value in highlighting both where consensus exists and where substantial uncertainty and divergence of opinions remain. Like the approach taken by Chrysafi *et al*. (2022) to estimate links between earth system processes, the ATIO expert elicitation would embed parallel expert elicitations in a workflow that looks to continuously and iteratively compile and synthesize understanding of pre-emergent innovations, with the results of each iteration of ATIO feeding back into data repositories of pre-emergent innovations and highlighting key gaps that need to be targeted in future rounds (Figure 5). A more detailed step-by-step description of an ATIO expert elicitation can be found in Appendix C.

MADAGASCAR
Rahova, a fish vendor, waits next to a boat with fish she bought from fishers earlier.

CHAPTER 7
EMERGENT SCIENCE, TECHNOLOGY AND INNOVATION INDICATORS

An emergent STI is defined as a new trend, innovation, application of existing technology, or novel technology, policy, institution or other innovation that has been introduced into real world use – beyond researcher-managed trials – in the last few years. These emergent STI can first appear as trending topics on social media, ideas being patented by entrepreneurs, companies recently funded through venture capital, or new grass roots efforts launched by farmers, fisherfolk, pastoralists, or other communities of small, informal AFS innovators. Data across STI domains at an emergent stage are often interconnected and can often have indicators that blur across multiple, if not each facet of STI. Furthermore, an STI may emerge in one place much earlier than it does in another location, and in different forms in different places. All this makes tracking emergent STI exceedingly challenging.

It is important to consider how STI and infrastructure drivers are reflected in the larger AFS discourse. Fanzo *et al*. (2021) identified two spaces where innovation occurs (Figure 6): food system supply chains and the distinct areas of production systems, storage and distribution, processing and packaging, retail and markets; and food environments, food availability and physical access, economic access, promotion, advertising and information, and food quality and safety. Understanding where in the AFS the STI fits is possible by leveraging artificial intelligence (AI) to surface and detect different types of technology and innovation and organizing them into a framework that emphasizes technological, social, political, economic and ecosystem innovations.

Information about emerging technologies that could be fit-for-purpose in LMICs will not emerge from one data source. The identification of any technology or service, no matter how promising, will need to be compared with data about feasibility at the country level and compared with those indicators, such as existing connectivity, electrification and roads and infrastructure.

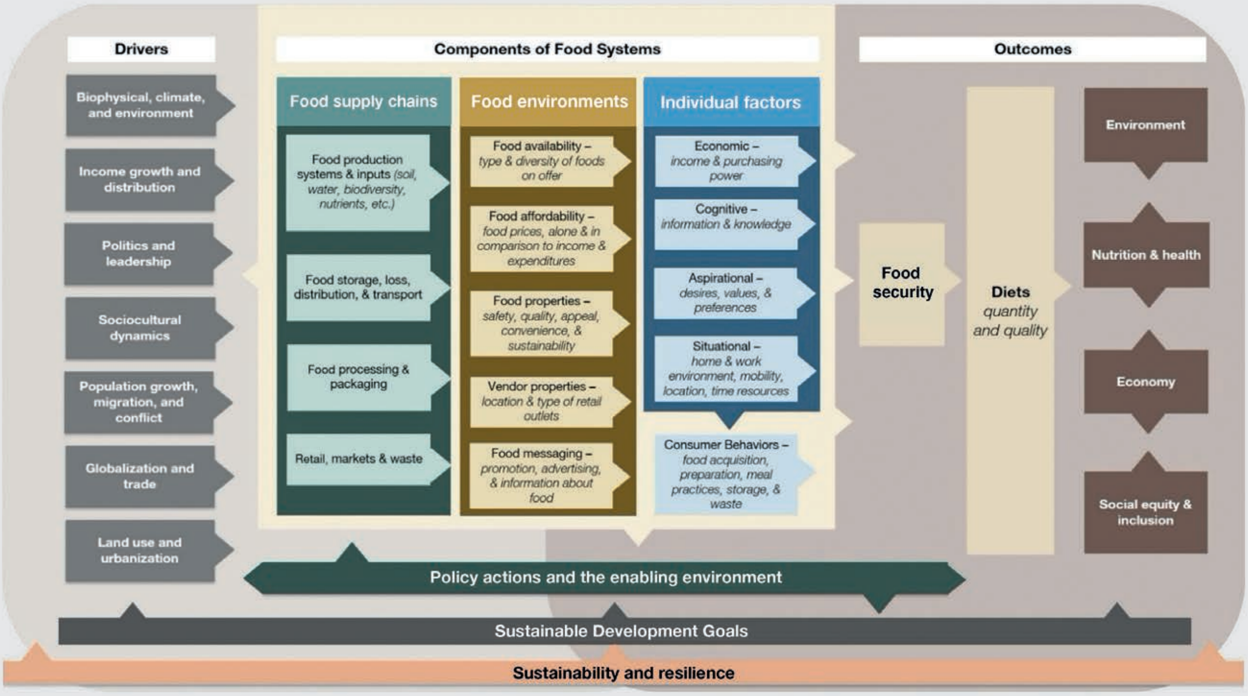
7.1 INDICATORS AND DATA SOURCES

Sixty-five data sources were assessed for relevance. Sources were then identified by type and placed into a broader indicator grouping (see Figure 7). Note that this is simply a demonstration of how ATIO could pursue data collection on STI via these methods; the approach would require modest adaptation for other types of innovations.

Commercial feasibility: The first indicator grouping centres around the concept of commercial feasibility – which focuses on the idea's market viability and ability to satisfy consumer demands or fulfil the role that it is intended to play (Queensland Government, 2019, https://www.business.qld.gov.au/starting-business/planning/idea/feasibility). Commercial feasibility can be assessed by looking across a range of source types, including patents and investment data.

- Patent data offer a rich source of information on innovation and have been used extensively as an indicator of innovation (Sampson, 2007). Some authors argue that the number of patents is a consistent and objective indicator to measure innovation, and that patent data offer both consistency and objectivity (Boone *et al*., 2019).

FIGURE 6 AGRIFOOD SYSTEMS CONCEPTUAL MAP



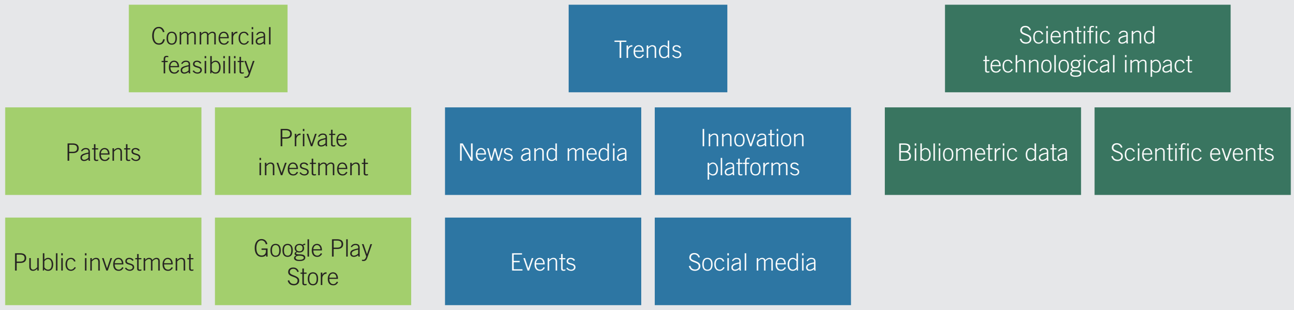
Source: Fanzo *et al.* 2021.

- Public and private investment data can illuminate emerging services and products and showcase new STI that are not fully matured in their ideation process but have enough of a business plan to garner some level of outside investment.
- The Google Play Store enables a look into applications that have proven commercial feasibility by being available in a public marketplace. Novel exploration of these databases could partially address the issues of identifying informal services that are emerging in LMICs.

STI can be readily identified for this indicator by tracking new patents, investment (private and public) announcements and updates, and data-mining application updates within the Google Play Store to identify newly added apps. Additionally, new information for commercial feasibility will be closely connected to how data and information for the following indicators are collated – for example, news sources identifying new major investments in STI could also appear in data sources that are reviewed for the trends indicator.

Trends: The second group of data sources can be categorized within a broader category of trend data. These are text-based sources that provide information about aggrotech innovations, technologies and science. Abstracting, grouping, and analysing the latest technological news can provide the most updated information about current AFS technologies on the market. This information can be used in combination with indicators from other groups to make decisions on emerging STI that are being discussed by experts and organizations.

FIGURE 7 INDICATORS AND THEIR DATA SOURCES



- Innovation platforms serve as a strong proxy for identifying trends in STI. These platforms offer a space for learning and change that works as a tool to support open innovation processes. They bring together different actors of the ecosystem in one place to identify solutions or to achieve common goals (Tui *et al*., 2013).

Tracking this indicator most prominently requires the regular review of news, media and innovation events/platform updates to ensure that diversity of sources and languages are included in the ATIO. Monitoring of high-level event agendas can also help identify new information about emergent STI trends. Any media review for the ATIO will be done in consultation with a communication/media specialist, to ensure that the results and research are meaningful (e.g. how to account for weight, sentiment, avoid double counting and targeting searches).

Scientific and technological impact: Data sources within this category are primarily related to scientific research done on the impact of AFS technology, assessments of technology adoption, and data/digital ecosystem analyses. For example, Sott *et al*. (2021) point out that augmented realities are still little explored in agriculture while technologies have been widely used in other sectors such as big data, blockchain and simulation/mathematical modelling. Additionally, Silva and Silva-Mann (2021) used bibliometric analysis to study the main topics on agriculture technology innovation that have grown the most in terms of scientific publication and classify techniques that can portray a long time and develop knowledge of science indicators and technology.

Like commercial feasibility and trends, this indicator requires a consistent monitoring plan to collate and update information about scientific and technological impacts. Using news and media sources, scraping of publisher and journal information and by attending and reviewing conference/event materials, new information for scientific and technological impacts can be identified and tracked.

7.2 DATA ACCESS AND AVAILABILITY OF DATA SOURCES

Access is a key feature for any type of data, structured, semi-structured or unstructured, to be used in the ATIO, but maintaining online resources requires significant computing infrastructure and curation resources. Use cases involving NLP and machine-learning (ML) models to identify innovations from academic databases and more than 25 grey literature sources have already been tested and validated in a focused collection published by Nature Research in 2020, Ceres2030: Sustainable Solutions to End Hunger (Acevedo *et al.*, 2020; Baltenweck *et al.*, 2020; Bizikova *et al.*, 2020; Liverpool-Tasie *et al.*, 2020; Maïga *et al.*, 2020; Piñeiro *et al.*, 2020; Porciello *et al.*, 2020; Ricciardi *et al.*, 2020; Stathers *et al.*, 2020). ATIO tested these methods across new, diverse data sources relevant for capturing innovation across the STI lifecycle, including patents, news sources, social media and other unstructured data.

Application Programming Interface (API) is a software intermediary that allows two applications to talk to each other. APIs are used to open their data and functionality for use by third parties. These services often indicate that the data are updated frequently (some, like weather data, in real time), data reuse and integration in other programs is permissible, and data extracted will be standardized—all important features when considering how to leverage multiple data sources for analysis on an ongoing basis.

As a proof of concept, a series of lightweight consultations was conducted for suggestions on where to identify relevant LMIC industry trend data and research about similar exercises focused on identifying data curation on innovation and technology in the agricultural field. Sixty-five prospective sources with existing APIs (Appendix D) were identified to determine how these new data sources could be leveraged alongside knowledge coming from academic and grey literature resources in the future using similar NLP methods. Ultimately, 19 of those selected were based on an assessment of:

i. Whether NLP techniques could be applied.
ii. Accessibility of data, there is a paywall or not.
iii. Identify the way and the type data are displayed.
iv. Frequency of updating of source.
v. Personal/professional opinion on quality of data.

Table 3 identifies a (non-exhaustive) range of sources available for the ATIO to draw on, providing an inventory to identify where to expect access issues regarding both subscriptions and whether an API is available. Sections of the table are included below, but the complete table is provided in Appendix D. Importantly, many of the resources that are marked as subscription or websites will require additional oversight and resources in the input pipeline and training data process. The evaluation process included examining whether a data source has an existing API, and if not, whether it was conducive to a process known as web-scraping, where custom code can be created to lift the information from the website. Other evaluation criteria included whether metadata are available, frequency of source updates, and whether AI could be used to derive insight. Appendix C contains more information about the resources.

7.3 IDENTIFYING EMERGING TECHNOLOGIES FROM UNSTRUCTURED DATA USING ARTIFICIAL INTELLIGENCE

The early identification of emerging technologies in agriculture is critical for the design and adaptation of new markets, policies, R&D, programmes, infrastructure and education. Detecting emergent agricultural technologies means more opportunities to discuss potential impact. It is well established that innovations from research can take years to develop and they often need to be in use for a long time before the direct and indirect benefits are fully realized. Further, innovations are often designed in a time that may look very different from the world in which they ultimately deploy — AFS technologies commonly take as much as 20 years to mature from an initial idea to measurable impacts at scale. The more one can surface relevant information about what early-stage technological innovation looks like, the more the future can be prepared for.

TABLE 3A DATA SOURCES FOR COMMERCIAL FEASIBILITY

Source	Source description
	Commercial feasibility
Google Patents Public Dataset	Google Patents Public Dataset is a collection of compatible BigQuery databse tables from government, research and private companies for conducting statistical analysis of patent data.
World Intellectual Property	As one of the 15 specialized agencies of the United States, World Intellectual Property lists of number of patent and property data sources for researchers on their website.
OECD REGPAT	The OECD REGPAT database includes patent applications to the European Patent Office (EPO) and Patent Corporation Treaty (PCT) by region. The patent filings linked to more than 5 500 regions using the inventors/applicants addresses
Wellspring Worldwide	Wellspring is a large company that provides technology transfer solutions worldwide. Wellspring acquired Flintbox, the world's largest online exchange of early-stage technologies.
AgFunder	AgFunder is a Agtech venture capital firm and they issue a report about investment in agrifood technology sectors every year.
S2G Ventures	A report which tracks macro-level trends, market dynamics and new innovations for sustainable food systems that is developed by an agrifood investment firm.
Pitchbook	PitchBook is a financial data and software company headquartered in Seattle. The paid access database provides information and business analytics about Venture Capital and start-up ecosystem worldwide.

TABLE 3B DATA SOURCES FOR TRENDS

Source	Source description
	Trends
World Agri-Tech Innovation Summit (March 22–23 2022)	World Agri-tech is the annual meeting place for the global agtech ecosystem, where agri-food businesses, investors and tech pioneers gather to exchange insights, be inspired, and identify future partners.
Techcrunch	A newspaper focusing on high tech and startup compaies, founded in June 2005.
Innovations News Network	A digital publication that provides free daily updates on global research, emerging science, policy and innovation.
FS Succesful Farming Technology News	An online news website. Its technology news section highlights news precision agricultural productsion and discovers the latest agricultural technology that could help farmers manage farm more efficiently.
Contexo	Contexto is one of Latin America's prime websites for tech, startups and venture capital news and data. They are a mediatech and data company covering the latest, most relevant tech and entrepreneurship stories from Mexico to Argentina.
Food and Farming Technology	An online news website that presents the technological breakthroughs in the growth, harvest, transportation, manfacture and retail of food. They present daily sustainable solutions to global audience of readers in the areas of farming, food production, machinery, software, electronics, engineering and financial services.
Agri Tech Tomorrow	An online trade magazine which provides products, companies, news, articles and events on the agricultural technology and precision farming industries with a focus on the new technologies likely to be commercialized.

TABLE 3C DATA SOURCES FOR SCIENTIFIC AND TECHNOLOGICAL IMPACT

Source	Source description
	Scientific and technological impact
USDA Research Strategy – Dashboard	The Research, Education, and Economics mission area of the United States Department of Agriculture has federal leadership responsibility for advancing scientific knowledge related to agriculture.
National Institute of Agriculture Research of Brasil (EMBRAPA)	Radar Agtech 2020/2021 is the second edition of this mapping of Brazilian Agtechs and Foodtechs. The document provides essential quantitative and qualitative information for the national agricultural innovation environment.
Israel Innovation Authority	An open innovation platform the Israel government launch calls for working on a particular project/solution.
Invest in Bavaria	Invest in Bavaria is the Business Promotion Agency of the State of Bavaria and Bayern International GmbH. It provides Interactive map with all the companies, cluster and start-ups from Bavaria (Germany).
Illinois Urbana-Champaign University	A crowdsourced list of startups that were founded by people who were part of University of Illinois
USDA	United States Department of Agriculture news, annoucements, and blogs related to agricultural technology.
Institute of Quantitative Social Science, Harvard University	Two published research papers with patent data included.
Digital Food Lab	DigitalFoodLab is a FoodTech insight and strategy consultancy for food and beverage companies.

Identifying emerging technologies from our ever-expanding universe of available, unstructured data requires a multistep process: understanding the problem, identifying and cleaning the data for use, creating or identifying the tools for analysis, running the analysis, model benchmarking and fine-tuning.

This involves synthesizing all the available scientific, technical and communication information spread across a variety of individual studies, news reports, patent documents, reports and much more. This can be difficult given the breadth and depth of human scientific research approximately doubles every nine years (Bornmann and Mutz, 2015).

New approaches, such as artificial intelligence, can help find patterns and make predictions to inform open-ended questions and analysis (see Figure 8). Applications such as machine learning/computer vision, which are frequently used to accelerate processing of big data, are particularly useful for tasks like data classification and clustering, image and speech recognition, predictive analytics, and information extraction. NLP is a field of machine learning in which computational machines are trained to understand text and spoken language.

Existing AI models developed by Havos Inc., a start-up launched out of Cornell University, were relied upon for this exercise. These approaches have successfully accelerated the process of systematic and scoping reviews, identified impacts and gaps from the organization's own evidence bases and project documents according to strategic plans, and contributed to the identification of misinformation on vaccine hesitancy from social media resources (Porciello *et al.*, 2020, Porciello *et al*. 2021a, Porciello *et al.*, 2021b). A key feature of the models is identifying AFS interventions from unstructured text, where specific phases can be recognized as discrete technologies, social or economic programmes, or ecosystem services and then organized within a larger taxonomy of interventions. Using state-of-the-art transformer models NER-BERT, the model does not need to have seen the specific intervention before to be able to detect it (Liu *et al.*, 2021). In addition to identifying emerging STIs, additional named-entity recognition (NER) elements, such as organizations, countries, populations, and plants and animals, can be extracted alongside interventions with minimal fine-tuning of the models. This creates a structured universe of data for analysis where none was before.

The similarity of interventions to emerging STIs is highly complementary and will require only small amounts of training data (per source) to fine-tune the models for use in ATIO. The feasibility and opportunities for scalability of machine learning to support detection of emerging technologies for ATIO was tested using sources and data structures that these models have not previously worked with, including patents, Twitter and web-based news sources without APIs. Other resources featured in the indicator table, such as individual private investment/high-level reports, innovation platforms, public data investment and Google Play have been successfully used in the pipeline and evaluated for similar parameters (e.g. digital agriculture interventions). The only resources that have not been fully tested are private investor databases, such as Crunchbase and Pitchbook that are behind a paywall. If access were provided and permission granted for use, the databases are similar in structure to other indexing databases and would be relatively straightforward to integrate.

7.4 DISCUSSION

Assembling real-world data from a variety of sources is an exciting and cost-effective opportunity to monitor and assess emerging technologies. Artificial intelligence has been under-utilized for bringing together large datasets and indicator frameworks and harmonizing those with new, or other, frameworks. For ATIO, this is mostly relevant regarding ensuring ongoing technical coordination between programmes like ASTI and IFSS Solutions Portal.

By evaluating a subset of the data available for emergent STI, this proof of concept showcases the value of using AL/ML for ATIO. It provides a consistent review of information for ATIO with the use of an automated data consolidation process.

The approach is scalable. New data sources can be added to the pipeline as the ATIO continues to evolve. This approach has been tested using unstructured data from various sources and time and research resources were saved while increasing the objectivity and analytical value of the data identified and evaluated. Given this, it is recommended that an AI/ML enabled approach be taken to aid the development of future ATIO outlooks.

The steps to identify, evaluate and build a pipeline to ingest relevant sources, demonstrate the feasibility of how to use machine learning to conduct topic modelling and information extraction are important first steps. To get at the level of resolution desired, however, additional resources for fine-tuning and training the model will be required.

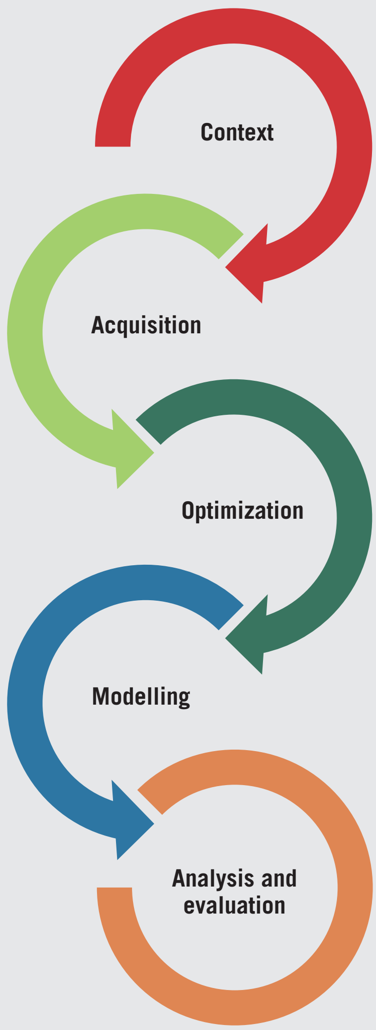
Finally, as is expected for a general pilot like this that does not have a particular focus, the topics identified general descriptions of things rather than a focused set of emerging innovations. This will improve as each ATIO report gets a more specific thematic or geographical scope. The proof of concept described here merely identified the steps of how this will work and demonstrated how to save time while increasing the diversity and the volume of STI data that can be reviewed.

7.5 IMPROVING THE USE OF ARTIFICIAL INTELLIGENCE FOR ATIO

There are limitations that are associated with using AI, which are highlighted while also describing opportunities for course correction.

First, high-quality data from sources like patents tend to emphasize emergent STI indicators that cluster around technologies for storage and distribution, processing and packaging, with some

FIGURE 8 **ARTIFICIAL INTELLIGENCE PROCESS**



information about innovations in food quality and safety and retail and market innovation, whereas news media and social media seem to emphasize relevant trends and social concerns. These results are shown in Appendix D.

This is especially important because datasets are not neutral but represent particular social and political norms, which can specifically affect marginalized groups. Certain steps should be taken to reduce bias in both the datasets and in the model input-output process, such as continuous feedback from expert trained labelling that have undergone diversity, equity and inclusion (DEI) training, as well as continually adding new data sources. The feedback can continuously improve model performance and accuracy while also reducing bias. ATIO must operate in a manner fully consistent with the Rome Call for AI Ethics.[18]

Machine-learning models are pre-trained using enormous datasets. There is increased interest

18 https://www.romecall.org/

in building awareness and documenting known bias in ML. When modellers use these datasets, they must be aware of the potential issues of the training datasets and course-correct by bringing in additional training data that can help correct these problems. ML methods can reveal patterns that would otherwise not be detected by the human brain alone, but the "interpretability" of the patterns depends on domain expertise (Murdoch *et al*., 2019). ML will almost always find a "pattern", but whether the identified pattern is insightful is not itself revealed by finding the pattern (Bishop and Nasrabadi, 2006; Marsland, 2015).

Finally, ML requires training to improve its overall accuracy. The training is typically conducted in the form of humans providing small amounts of feedback by labelling data in what is known as a supervised learning approach. To test the accuracy of the process, data are extracted from the model and randomly split into batches; some of the data are reviewed and corrected, whereas some are held aside for testing. This process is described in Appendix D.

A robust data strategy that incorporates various data sources can help reduce bias in both inputs and outputs. Other opportunities to reduce risks include using a semi-supervised learning approach, where human experts are reviewing and correcting the data at randomized intervals and returning the corrected data into the model. An important consideration is to ensure human reviewers are well-trained in diversity, equity and inclusion (DEI) and have been trained to identify issues with dataset and model output.

KYRGYZSTAN
Workers in a greenhouse farm, where planting of seedlings and harvesting of vegetables take place in the village of Uchkun, 25 km from Bishkek.

CHAPTER 8
MATURE SCIENCE, TECHNOLOGIES AND INNOVATIONS

There is potentially a wide range of mature STIs due to the speed of innovation and widespread adoption across countries. ATIO categorizes mature STIs into primary production; post-harvest technologies; processing, manufacturing and packaging; labour; and consumer-facing food environments. Note that mature STI can include not just new products, but equally policy, institutional, financial or other social innovations. Many elements within each domain listed in Table 4 potentially demonstrate the wide range of options to address the diverse, context-specific set of agrifood system challenges (Herrero *et al.*, 2020). While these are not comprehensive, they represent major areas of pre-existing data collection across the entirety of AFS STIs (Glopan, 2016; World Bank Group, 2019). Tracking mature innovations could potentially give insights into issues of sustainability and equity across AFS, however further analysis would need to be undertaken to assess the uptake and coverage of those STIs in different contexts, among different users, and in different political economies. FAIR (Findable, Accessible, Interoperable and Reusable) data principles will be important, perhaps especially in documenting the diffusion of mature STIs.

A stocktaking was done of the types of data that capture the range of technologies and other innovations that might reasonably be considered mature in their development and adoption. This is – or at least should be – the most established space in which there exist plentiful data to track the adoption and use of AFS STI across countries and over time. However, major data gaps remain, and the diffusion of most mature STIs remains incomplete. Most of the data sources that were considered relevant, accessible, and of higher quality were in the primary production grouping. In contrast, there were no data sources that met ATIO's criteria in the consumer-facing food environments and consumer behaviour categories. In post-harvest, processing, and labour groupings, across a range of data sources investigated, only three were found viable according to the inclusion criteria set (discussed previously in section 5).

As a reminder, six basic criteria were set for the inclusion of a data series in a prospective ATIO:

1. Data are available at country level to permit internationally disaggregated analysis.
2. There exist adequate recent data, meaning the series includes at least one data point from 2016-present for a larger number of (>50) countries.
3. The data series is inclusive, meaning strong (not necessarily universal) coverage of LMICs.
4. The data source is reliable, meaning it is grounded in accepted scientific theory and practice, uses peer-reviewed processes, comes from respected/credible organizations, etc. – include no advocacy group or journalistic material.
5. A clear conceptual correspondence exists between the data series and AFS STI inputs.
6. The data source offers a clear, credible, interpretable, sensible definition of the variable.

It was also required that the data be publicly accessible free of charge.

For each data series identified, data were compiled to describe the variable, its name and definition, its source, the number of countries for which observations are available, the number of countries for which at least one observation is available from 2016-present, and any other salient information on

TABLE 4 MATURE SCIENCE, TECHNOLOGY AND INNOVATION DATA STOCKTAKING PERFORMED ACROSS VARIOUS ELEMENTS OF AGRIFOOD SYSTEMS

Primary production	Post-harvest	Processing, manufacturing, and packaging	Labor	Consumer-facing food environments	Diets and nutrition
Improved seed (1,1,1)	Improved storage bags (2,2,0)	Fortification regulations (1,1,1)	Occupational health and safety protections	Electronic food assistance (3,3,0)	Acceptance of insects
Fertilizer (2,2,2)	Improved storage facilities	Reformulation regulations (5,2,1)	Agriculture labour employment (1,1,0)	Nutrition labeling	Phone apps to track diet
Pesticides (2,2,1)	Commodity exchanges	Sustainable/ recyclable packaging	Minimum wage laws apply (3,3,1)	Modern grocery retailers and supermarkets (1,1,1)	
Recuced tillage (2,2,1)	Biodiesel production (1,1,1)	Transportation (1,1,0)	Forced labor	Cashless retail (1,1,0)	
Vertical farming ops	Supply chain and infrastructure (1,1,1)	Energy-efficient waste disposal (1,1,0)		Farm-to-table marketing apps	
Plant-based/Cellular meat ops and proteins (1,1,1)	Internet access (2,1,2)			Food loss recovery programmes	
Cultivated land irrigated (2,2,1)				Food Sensing Technology	
Aquaculture (2,2,1)					
Animal health/ genetics/nutrition (2,2,1)					
Livestock feed additives					
Extension services (1,1,0)					
Precision ag machinery (1,1,0)					
Laser land levelling technology					
Cultivated area in cover crops (3,3,0)					
Plant-based proteins (3,3,0)					
Power irrigation (2,1,0)					
Energy use (1,1,0)					
Improved water resources & quality (3,2,0)					
Improved soil quality (3,2,0)					
Forestry (1,1,0)					
Physical investments (1,1,1)					
Total Factor Productivity (1,1,1)					

Legend

- Includes relevant indicator(s)
- Includes no relevant indicator(s)
- Search yielded no result

Note: Numbers in parentheses represent the numbers of (indicators/data series/number of prioritized indicators), respectively. Detailed descriptions of the indicators are reported in Appendix A.

that specific variable and data source.[19] It was then assessed whether the data series satisfied all six of the above inclusion criteria. If so, the series was designated for prioritization for inclusion in ATIO. A second assessment was done to confirm, refine or challenge the original assessment for double entry confirmations of the data series deemed of satisfactory quality to merit inclusion in ATIO. The analysis was not aligned around AFS outcomes as it would be challenging to establish causal pathways of STIs to specific outcomes such as nutrition, environmental sustainability, livelihoods, etc.

In the case of mature STIs, 57 indicators and 50 data series were identified from various sources, including FAOSTAT, OECD, World Bank, and other public and private-sector databases. As shown in Table 4, only 17 subareas of AFS were found to have viable datasets or datasets that met the inclusion criteria. Most datasets fell in the areas of "primary production" and "processing, manufacturing, and packaging." There was only one viable dataset in the "consumer-facing food environments." Of the 57 indicators, only 17 were prioritized using ATIO's criteria. Within primary production, there are several datasets hosted by FAO, including fertilizer and pesticide use, land area equipped for agriculture and aquaculture. Some datasets related to plant-based and alternative proteins, and controlled environment agriculture, are an interesting tech space to watch. In the area of postharvest, OECD has a dataset on biodiesel production. Several databases captured technologies related to fortification and reformulation of food products and two datasets by FAO that provide data on transportation and waste disposal. The GlobalWage Indicator, OECD, and ILO host datasets on minimum wage laws, and there are no datasets or data that did not meet the criteria for the demand side of AFS, indicating a call for more R&D to track the various technologies that are being carried out in these areas. Most of the value addition happens post-farmgate (Yi *et al.*, 2021), however, most data concern primary production on farm.[20]

There are significant STI data gaps. These are especially evident in post-farmgate components of AFS. Processing, packaging and retail setting data, where there is a range of potential technologies, has significant database and indicator gaps. For example, there is a range of mature technologies available in food environments – using crowd-sourcing technologies to track food purchases, QR codes to track ingredients, user-interfaced nutrition and environmentally sustainable labels. There also exists a range of STIs on diets, nutrition, and health such as personalized nutrition applications and alternative environmentally sustainable tech growth. For formalized "built" food environments, such as hypermarkets, supermarkets and other growing retail types, the types of consumer-facing mature STIs is expansive but not systematically tracked (Downs *et al.*, 2020). However, most of these consumer-facing mature technologies are out of reach for low-income contexts. There are also gaps in STIs across the policy interfaces, ecosystems and institutions; financial innovation; and STIs that cut-across gender issues and empowerment. In fact, very few indicators that measure STIs can be disaggregated, again making it difficult to assess inequities.

Another gap is that some substantive data fail to reach scale because the platforms, infrastructure, and data-sharing services are not in place to fuel data use—the process of "datafication." Data accessibility does not necessarily equal data usability, insofar as using the data for decision-making requires some form of technological interoperability. Porciello *et al.* (2021a) highlighted that "due to weak infrastructure and limited resources, most countries cannot prioritize establishing and maintaining online resources.

For example, annual crop variety information is valuable data for multiple agricultural value chain actors as well as farmers. But currently, most national crop variety catalogues containing

19 Variations on the same underlying variable are treated as a single data series. That is, the current dollar, constant dollar, current local currency values of a measure (e.g. agricultural R&D expenditures) are all treated as variants of a single data series, as are variants of those measures reflecting intensity relative to, for example, agricultural output, population, or land size. All derive from a single core measure, the nominal agricultural R&D expenditures in a country each year. Because the number of transforms of that variable are numerous, the single root variable is adopted.

20 New datasets emerge occasionally through the efforts of individual research groups and may be useful, at least temporarily, but lack an institutional platform for ongoing data maintenance to keep the series up-to-date. An example that emerged after this report was drafted is the Ludemann *et al.* (2022) dataset on crop-by-country fertilizer application.

country-level data that farmers in sub-Saharan Africa use to make seasonal crop selections are still print-based. While digitizing crop variety catalogues is the first step, it will not necessarily result in more opportunities for greater uptake of new varietals. For that to happen, a platform with information about the varietals, their traits, and inventory would need to be connected to seed chain supply chains and/or farmers. See Box F for more on the potential to create and invest in a crop variety database.[21] ATIO can help identify such data needs and opportunities for prioritization by stakeholders.

To take a holistic AFS approach, as opposed to focusing on farm production STIs alone, it will be important to work towards data that capture STIs across the entirety of AFS. This will require efforts outside ATIO to address key data gaps. FAO could play an important role, working with partners to fill these gaps – e.g. government ministries independent research groups working globally – not only in working with a range of retail-oriented companies and packaging and processing companies to track better how consumers are using these technologies in food environments, mobile phones, and where health and food systems interface, but also to build the infrastructure and shared services of these data.

21 We thank Dr E. Mabaya of Cornell University and The African Seed Access Index for drafting the original version of Box F for this report.

8.1 ACCELERATING THE ADOPTION OF PRE-EMERGENT AND EMERGENT INNOVATIONS

AFS transformation requires proactive engagement with issues of social licence and acceptability in STI adoption and diffusion, as well as much greater use than has been typical to date in employing responsible innovation principles, and greater investment in public dialogue. This societal conversation is required to ensure that the values and motives of different stakeholders are transparent, as different pressures from consumers, employees, investors and governments can push innovation in different directions, sometimes with adverse consequences. Without such engagement in responsible innovation, potentially powerful STI may go unused, not adopted nor scaled despite considerable potential for impact. STIs might be introduced that inadvertently (but predictably) worsen the problems that need to be solved. The AFS transformation necessary to tackle societal grand challenges might then be constrained by those who trade on business as usual.

Herrero *et al*. (2020) proposed eight actions to accelerate the sustainable and responsible adoption of pre-emergent and emergent technologies, depicted in Figure 9. Three of those (building trust, transforming mindsets and enabling social licence) comprise individual and collective social aspects of stakeholders and potentially increase the demand for innovation. These are very much tied to establishing “the rules of the game” by increasing the openness and acceptance of the values of both the providers and users of innovation, and the acknowledgement that radically different futures could emerge from the implementation of the innovations. This is also related to the much-needed social licence and increased transparency of the potential impacts and consequences of the technologies.

FIGURE 9 ACCELERATORS OF AGRIFOOD SYSTEMS TRANSFORMATION

Source: Herrero *et al.* 2020.

Trade-offs and undesirable effects inevitably emerge from the deployment of new technology and innovation (Herrero *et al*., 2021). Intentional planning to anticipate and address impact pathways on multiple AFS outcomes are required to obviate adverse, unintended impacts of AFS STI.

A dynamic enabling environment is required for supporting the discovery, testing and implementation of new STI for AFS transformation. Three critical elements representing this needed dynamism are agile market incentives and conducive policies and regulations that will reduce entry barriers in innovation markets. Recognizing that many of the innovations require sustained investment beyond short project cycles, stable and sustained finance is required to ensure that innovations come to fruition. The identification and assembly of bundles of complementary innovations, including all the technological and social elements required for success in multiple dimensions of AFS performance, are essential for planning transition pathways for accelerating AFS innovation and transformation (Herrero *et al*., 2020, Barrett *et al*., 2022a).

BOX F THE CASE FOR A CROP VARIETY DATABASE

Before a new crop variety can be commercialized, in most countries, it must go through a formal "variety release process" in line with the national seed regulatory framework. The process involves the evaluation of the variety through a prescribed trials system, a careful review of data by a technical variety release committee, and the registration of the variety in an official variety catalogue. These "national performance trials" (NPTs) are designed to test new crop varieties for performance compared with varieties currently in the market, thereby proving "value for cultivation and use" (VCU). As a result of the variety release process, for every variety that is available for commercialization, there are public records that characterize the identifying features as well as performance indicators across multiple indicators. Yet critical data sources are still woefully mired in the past. Information on available crop varieties is scant, rarely online, and mostly provided through irregular print copies of national variety catalogues, or simply word-of-mouth. This data gap presents a unique opportunity for Agrifood Systems Technologies and Innovations Outlook (ATIO) to establish a Crop Variety Database (CVD) that will serve as a dynamic, multilingual, and interactive online platform where anyone can find reliable varietal information on key cereal, legume, vegetable and vegetatively propagated crops in low- and middle-income countries (LMICs) – perhaps especially neglected and underutilized species. Access to timely, comprehensive data about improved crops is more important now than ever before for sustainable agrifood systems (AFS). It allows farmers to adapt quickly to climate change and combat ongoing threats from pests, disease, and weeds. Table 5 outlines potential uses of this database by different stakeholders.

TABLE 5 USER ENGAGEMENT AND BENEFITS OF CROP VARIETY DATABASE TO DIFFERENT STAKEHOLDERS

Community	How will users engage with and benefit from the platform?
Small-scale producers and consumers	▸ Identify suitable varieties that can meet their needs ▸ Link variety-specific information to farmer advisory services ▸ Share variety-specific user experiences with other farmers and researchers
Research organizations	▸ Up-to-date information on variety registry and commercialization ▸ Share information on recently released varieties and pipeline (product development) ▸ Reference database for research and publications on agricultural R&D
Seed companies	▸ Share information of commercially available varieties Feedback on variety performance from end-users (farmers and consumers) ▸ Learn of potential new markets to target their varieties
Government and development partners	▸ Real-time intelligence on available crop varieties Information can be used for design and implementation of input subsidy programmes ▸ E-Extension: Disseminate variety-specific crop husbandry information

»

BOX F (Continued)

Existing coverage
Currently few resources exist with reliable crop variety information, and even fewer that focus on Africa. Online resources about Africa, such as the COMESA Plant Variety Catalogue and the SADC Center Variety Catalogue, have limited variety data, no historical data before 2016, and are expensive to register. This is in part because those catalogues were designed with the primary goal of registering varieties to safeguard plant breeders' rights. Other systems, such as the European Union plant variety database, do not include any information about low- and middle-income countries (LMICs). The International Service for the Acquisition of Agri-biotech Applications (ISAAA) only tracks genetically modified varieties. The proposed CVD will deliver in areas overlooked by existing entities and create a data hub for all stakeholders to access relevant information about crop varieties. In partnership with Cornell University, the Africa Seed Access Index (TASAI) has started to digitize crop variety information that is available from national variety release catalogues (see https://tasai.org/ for details). However, the scope of this project is currently limited to 22 sub-Saharan African countries with a focus on only four staple cereal and legume crops per country.

Approach to gathering/curating data on a global basis
As mentioned above, data and information on commercially available crop varieties gathered through the variety release process are often publicly available through national variety catalogues. However, this information is neither digitized nor standardized. Moreover, different languages are used depending on the country's context. With modest resources, ATIO could establish an interactive universal database with detailed information on every crop variety as illustrated in the text box below. This information will be gathered through the following networks, institutions, or groups: national variety release committees, CGIAR centres, plant breeders, public extensions officers, seed companies, seed trade associations, agro-dealer networks, etc. After initial set-up, the database can be maintained by authorized editors through a wiki platform for long term sustainability.

What information users can expect to find on CVD for a specific bean variety

- **Names:** Formal name of variety, local names used by farmers, variety origin.
- **Phenotypic characteristics:** Images and descriptions of identifying features including size, colour, shape, the smell of the plant, pod and seed.
- **Performance:** Yield levels, nitrogen fixation, foliage palatability for livestock.
- **Biotic and abiotic stress:** Disease resistance (root rot, leaf blight, bean common mosaic virus and cucumber mosaic virus), water requirements, heat tolerance, frost resistance.
- **Crop husbandry:** Optimal spacing, location-specific growing calendars, recommended fertilizers, etc.
- **Nutritional data:** Nutrition (protein, biofortification, micronutrients), cooking time.
- **Commercialization:** Years when variety is commercially available, names of companies selling a variety.

MONGOLIA
The life of a livestock herder defies the challenges brought by Mongolia's climate – summers are very hot and dry and winters bitterly cold. But over the past two decades, climate change has made what's known as a dzud more severe and more frequent.

CHAPTER 9
EVIDENCE SYNTHESIS FOR INTEGRATED IMPACT ASSESSMENT

Stocktaking of AFS STI from inputs through diffusion at scale is not the purpose of ATIO. Descriptive evidence on the current state of AFS STI across its life cycle – of the sort described in the previous four sections – is necessary to guide transformational investment and policy. But given scarce resources, descriptive evidence is often insufficient to induce investments in the absence of credible predictive or inferential evidence on the likely impacts of AFS STI. There is great value to assessing not only what STI diffuses and scales, but equally the likely or observed impacts from diffusion and scaling.

The vision of ATIO is to help foster accelerated AFS transformation to attain multiple goals: efficient and sustainable use of scarce resources, prosperous and equitable livelihoods for farmers, workers and enterprise owners throughout the AFS, healthy and safe diets for all persons, and resilience to shocks and stressors. STI must be assessed with reference to those intended impacts. Especially in LMICs, where scarce financial and human resources limit investment and where trade-offs among competing objectives can be substantial, impact assessment evidence can induce additional investments and guide wiser, more impactful private and public sector decision-making.

Unfortunately, impact assessments are complex, expensive, and time-consuming, and therefore relatively scarce. And a wide array of researchers and organizations generate impact assessments, using an array of methods, publishing their findings in diverse outlets (and languages), in an uncoordinated fashion. The distributed nature of impact assessments of variable quality poses challenges to well-informed decision-making around AFS STI.

The last essential component of ATIO is therefore evidence synthesis for integrated impact assessment. As mapped explicitly in section 6, when considering pre-emergent STI, the process of developing each ATIO report should compel active discussion throughout stakeholder networks of the available evidence on the prospective or demonstrated, actual impacts of various AFS STI. This requires collecting and curating available evidence on specific STI, individually and in contextually suitable bundles. But as discussed in sections 4 and 7, bringing together information from a range of sources – transcending language, disciplinary, organizational barriers and publication formats – is a complex task given the volume of new scientific evidence generated each day. Information and library scientists have developed – and are continuously refining – a range of formal evidence synthesis methods to facilitate the unbiased identification, collection and integration of data from diverse sources.[22]

While evidence synthesis had become commonplace in fields as diverse as biomedical and health policy, social policy and environmental management, these methods' applications to AFS remain relatively new. There have been a few high profile, time-bound efforts in this space. The Ceres2030 project (Laborde *et al.*, 2020) published a collection of evidence synthesis studies in the *Nature* journals (https://www.nature.com/collections/dhiggjeagd/). The Systematic Reviews for Animals & Food (SYREAF, https://syreaf.org/) project curates a range of systematic reviews, especially from animal and veterinary sciences, and even maintains some "living systematic reviews", i.e. web-based systematic reviews that are updated frequently to incorporate new evidence as it becomes available. CGIAR's Standing Panel on Impact Assessment (SPIA) coordinates and

22 Cornell University Library, a global leader in evidence synthesis, offers a good overview at https://guides.library.cornell.edu/evidence-synthesis.

hosts a range of impact assessments related to AFS STI linked to CGIAR research. The Agricultural Technology Adoption Initiative, a collaboration between MIT's Abdul Latif Jameel Poverty Action Lab and UC Berkeley's Center for Effective Global Action, has funded and hosts the results of a variety of academic impact evaluation related to agricultural technologies. And the ICONICS project at the University of Washington has looked to extend efforts to document the use of global scenarios (shared socioeconomic pathways – SSPs) developed for the IPCC and used in a wide range of global agrifood assessments. But ongoing evidence synthesis across the broad array of AFS STI thus far remains absent.

As explained in section 3 (Figure 2), the STI life cycle stage maps to the methods used to try to assess impact. Until an STI has emerged from laboratories, experiment stations, farmer fields, communities, or other sources, all impact assessment is necessarily *ex ante* of uptake, i.e. based on simulation modelling, whether the model is explicit or implicit (i.e. a mental model), quantitative or qualitative. *Ex ante* impact assessment is useful even after STI has emerged, not least of which as a part of foresight exercises to try to understand how impacts might vary across different possible AFS futures (Thornton *et al*., 2018; Wiebe *et al*., 2018; Barrett *et al*., 2021a) or to explore unintended consequences and the effects of complimentary policies and regulations.

As new STI emerges in practice beyond researcher-controlled trials, *ex post* impact assessment begins to play an essential role in rigorous evaluation of the real-world outcomes attributable to a specific (or bundle of) STI. For mature STI, *ex post* impact assessment methods become viable, even desirable, often using rigorous research designs such as randomized controlled trials (RCTs), although not all STI lends itself to rigorous *ex post* impact assessment using RCTs or quasi-experimental methods, however (Barrett and Carter, 2010, 2020; Barrett, 2021b). Rigorous *ex post* impact assessment has attracted considerable attention in recent years, both in one-off evaluations undertaken by various organizations and investigators and as a part of broader research programmes. A range of groups specialize in *ex post* impact assessment, including the International Initiative for Impact Evaluation (3ie), the World Bank's Development Impact Evaluation (DIME) group and the Campbell Collaboration. But none of these focus on – and typically they have patchy, opportunistic coverage of – AFS STI. Moreover, because sampling and measurement error necessarily cast doubt on the generalizability and reliability of even well-done single evaluation studies, replication is needed to build a convincing evidence base. Evidence synthesis products, including scoping or systematic reviews or statistical meta-analysis of the body of impact evaluation evidence, can shed useful light on what reliably works, where, and under what conditions.

The multiplicity of desired impacts from AFS transformation also necessitates paying explicit attention to trade-offs among different goals. No STI generates favourable impacts in every domain; all involve both positive and negative spillovers on other desirable outcomes given the closely coupled nature of AFS (Herrero *et al*., 2021). It is therefore wise to incorporate trade-offs analysis explicitly into both *ex ante* and *ex post* impact assessment (Kanter *et al*., 2018; Antle and Valdivia, 2021) and at varying spatial scales from global assessments (Hasegawa *et al*., 2018; van Meijl *et al*., 2018; Rosegrant *et al*., 2017) to national (Sain *et al*., 2017) and local assessments (Valdivia *et al*., 2017). The multiplicity of prospective impacts of AFS STI – from productivity to gender to nutrition outcomes – also necessitates the inclusion of a wider array of perspectives to understand potential challenges to scaling better, as well as vulnerable populations' risk exposure to unintended consequences. Evidence synthesis can build on participatory foresight approaches that attempt to incorporate a greater range of alternatives and wider uncertainty systematically (Trutnevyte *et al*., 2016; Vervoort *et al*., 2014; Zurek and Henrichs, 2007).

Especially when combined with *ex ante* impact assessments, integrative impact assessment efforts can generate powerful evidence to inform policymakers about AFS STI options. The participatory process through which the pre-emergent and emergent STI data development will occur creates a natural opening to prioritize the domains for which evidence synthesis seems especially valuable. ATIO will enable strategic, rather than merely opportunistic, evidence synthesis around AFS STI.

UNITED REPUBLIC OF TANZANIA
A Tanzanian scientist analyzes different seeds with a microscope in a laboratory at a Tanzanian Forest Service tree nursery and seed centre in Morogoro.

CHAPTER 10
SUMMARY INDICATORS BY COUNTRY

The ATIO approach of integrating data throughout the STI life cycle implies a degree of complexity, which often works against data and analysis effectively influencing policy. Many indicators exist for the initial inputs to generating new STI, through horizon scanning and foresight to track the evolution and prospective impacts of pre-emergent and emergent STI, to monitoring and evaluating mature STI diffusing at scale. Some country-specific indicators are available, but many other (especially pre-emergent and emergent) STI lack such geographic specificity.

Evaluating the performance of and guiding policy for a country based on a wide range of indicators is sometimes difficult and fraught with issues like subjective selection of preferred metrics. Summary, scalar-value (i.e. single number) indicators like indices and scores are frequently used as composite metrics of many variables to provide users with a simpler, single parameter for evaluating progress and benchmarking against other countries. The hope is to reduce a complex mass of evidence to a single indicator reflecting the latent concept of interest, in the case of ATIO, the outlook for AFS technologies and innovations in that country.

Many notable examples of these kinds of metric exist across different domains. For example:

The United Nations Development Programme's *Human Development Index* (HDI) measures average achievement in key dimensions of human development: a long healthy life, being knowledgeable, and having a decent standard of living. It is constructed from normalized indices for each of those three components, spanning multiple specific measures. The *Notre Dame Global Adaptation Index* (ND-Gain) ranks the climate adaptation performance of 177 countries. Like the HDI, ND-Gain constructs a measure from a set of subindices built from dozens of individual indicators. Other indices have been constructed for assessing any of several latent concepts that link to AFS performance or outlook, including the capacity of a country's veterinary services (OIE VSI) or the vulnerability of smallholders to climate change (Thornton *et al*., 2018).

The *Global Innovation Index* (GII) of the World Intellectual Property Organization (WIPO) and UNCTAD's Readiness for Frontier Technologies (RFT) are two of the few indices directly linked to global innovation. Although not focused on AFS, GII and RFT evaluate the performance of economies around the world in terms of innovation and frontier technologies, respectively. These are single-value measures. GII is based on the arithmetic average of 80 normalized indicators, including measures of political environment, education, infrastructure and knowledge creation. RFT rankings are based on subdomain rankings around ICT, skills, R&D, industry and finance.

10.1 SUMMARY INDEX CONSTRUCTION METHODS

A range of methods for constructing summary indices has been developed in the literature. The main methods include:

Simple ranking or scoring systems: This is the most common method and usually involves a group of experts ranking a given set of variables in

Pros	Cons
▸ Simple summary of many variables ▸ Easy to use for benchmarking and ranking ▸ Widely used by many stakeholders ▸ Standard construction and data input ▸ Promotes comparability and transparency	▸ Index can be driven by 1–2 key variables ▸ Loses lots of information, removing detail ▸ Valuable for many users require ▸ Unweighted indices do not reflect variables' importance but weights are subjective ▸ Statistical metrics often complex to explain

ascending order. The ranks of the different experts are then added and the cumulative position of the variable is then used as a final index for comparative purposes. Herrero *et al*. (2020, 2021) used this method for ranking the potential impact of AFS innovations on the sustainable development goals. Similarly, NASA's Technology Readiness Index is a simple scoring system based on a 9-point scale.

Simple arithmetic systems: The use of scoring systems involves the computation of arithmetic or geometric means of many normalized variables. In its simplest form, this method gives equal weights to all groups of variables. However, in many instances weights are used to increase the relevance of a set of variables, depending on the type of question the index will be used for. A good example of the use of this method is the UNDP HDI.

Indices based on advanced statistical methods: The use of simple indices are in many cases based on highly correlated variables. Hence, more advanced statistical methods like factor or principal component analysis are used to develop normalized indices. These methods reduce the complexity of the problem by aggregating sets of correlated variables into a few new, uncorrelated variables. The normalized scores of these new variables are then used to construct an index for each observation or country. Good examples of this method include UNCTAD's RFT index and the climate vulnerability index produced by Thornton *et al*. (2018).

Should the ATIO include an agrifood technology and innovation index?

It is technically feasible to derive an agrifood technology and innovation index with the available data, metrics and methods. The literature abounds with examples of their construction and implementation, but with different degrees of success in their subsequent adoption.

Should the ATIO include such a summary index? There are pros and cons to using a summary index measure to try to represent the outlook for a country's AFS STI in a single measure.

The main constraint of such indices lies in the collapse of rich information and metrics into a single number and the potential manipulability of those summary measures. Different stakeholders with different values and lines of enquiry require different metrics and information. Agreeing on a weighting scheme for a wide range of measures can be difficult because the use cases vary among users. Particularly for AFS innovation, spanning from production to consumption throughout the complex feedback intrinsic to systems, it may be meaningless to summarize performance metrics, as it would be difficult to pinpoint the AFS component(s) to which the metric refers. More specificity will always be required to develop actionable solutions to accelerate progress in AFS STI in some countries. While summary rankings hold obvious appeal for policymakers looking for a simple metric, that simplicity is too often misleading. Hence, building a summary index for the ATIO is not recommended; instead highlighting performance and outlook in specific, measurable, and actionable domains is favoured.

AFGHANISTAN
Afghan farmers throw wheat sheaves into a threshing machine in Kuz Kunar district of Nangarhar.

CHAPTER 11
A CONSORTIUM DESIGN FOR ATIO 2024 AND BEYOND

ATIO represents a major undertaking. There already exist multiple parallel efforts that tackle different data collection, curation and analysis activities, as enumerated in prior sections of this study. However, to date, no end-to-end tracking of AFS STI exists across the whole STI life cycle, from the inputs into R&D through the pre-emergent and emergent phases – which often last years, even decades – to the diffusion and impacts of mature STI. Building the global public good of a curated, end-to-end data source on AFS STI will require a sustainable collaborative structure that draws together partners with expertise throughout AFS and the world.

A consortium model has several desirable attributes. First, it can draw on the distributed expertise that already exists in the global research community around AFS STI. Second, a consortium model can reduce wasteful duplication of effort and confusion among end users that may arise without adequate coordination among the various parties already active in one or another component of the global public good that ATIO would represent.

As the UN specialized agency for food and agriculture, FAO is a natural coordinator of a consortium of partners working together to produce high-quality, scientifically rigorous, publicly accessible, open access data products and analyses to inform public and private sector decision-makers. But the task is too vast for FAO to tackle on its own. It needs to tap scientific partners to assist, especially with the more technical aspects of an ATIO. Many organizations already have invested considerably in building data collection and analysis teams and protocols, relationships with unstructured or semi-structured data providers, or other fixed costs that are valuable and could be lost if their platform were not adequately incorporated into the ATIO effort. There is a substantial amount of work to be done to fill key data gaps, to develop and validate credible indicators for intrinsically unstructured data, and to graduate more data series from the semi-structured or unstructured state in which many organizations hold relevant data to the structured data format that makes information readily usable by a wide range of audiences, perhaps especially those with sparser technical teams to analyse data, as in many LMIC governments, non-profit organizations and civil society organizations.

There is another reason for a consortium model: to create a firewall to safeguard the integrity of the product. A successful ATIO will necessarily influence public and private investment patterns worldwide. For both political and financial reasons, powerful actors might wish to influence the assessments reported in ATIO. The WIPO's *Global Innovation Index* is organized to guard against such issues. *GII* is a co-branded product centrally managed and sponsored by a unit within WIPO, a UN agency, but with the technical work subcontracted out to partners in its consortium, mainly a lead research partner. The co-branding and insulation of the technical work from the more public-facing focal point of an inherently political (UN) organization provides the best of both worlds: the advantage of a clear lead brand and the safeguards or external expertise. There is merit in the design of the WIPO GII model for those various reasons.

With reference to Figure 2, which mapped different data types to different stages of STI life cycle, at least two distinct groupings of activities are envisioned in which distinct partners might specialize:

1. **Collection, curation and analysis of data on STI inputs and mature STI:** FAO would lead this component of the activity, given FAO's unsurpassed access to government statistical systems and existing strengths in this domain.

Several STI inputs data collection activities currently exist outside FAO on which ATIO could potentially build. Existing efforts at compiling essential STI input data must be maintained. Losing existing data collection platforms and expertise, such as that within ASTI, would be a major setback. As described in section 5, OECD compiles such data for its member states and on major emerging markets. The International Science and Technology Practice and Policy (InSTePP) programme at the University of Minnesota has built up an impressive collection of data in this space, especially on rates of return to STI investments. But those data are not publicly available, nor open access. InSTePP data series were therefore omitted from the AFS STI indicators included in section 5, although it would be worth exploring the possibility of building on those data. As One CGIAR launches new research initiatives, including prospectively one around Foresight and Metrics, there may be an opportunity to reinvigorate the collection, curation, and analysis of timely, open access, structured data on STI inputs and *ex ante* assessment of their possible impacts.

Once, this was largely the domain of the International Service for National Agricultural Research (ISNAR). After ISNAR closed in 2004, some of its activities continued under the auspices of the International Food Policy Research Institute (IFPRI). Today, those are mostly reflected in IFPRI's Agricultural Science and Technology Indicators (ASTI) project, which generates the largest collection of STI input data on LMICs. ATIO could afford an opportunity to expand the geographic and indicator coverage of ASTI data and update series, drawing on FAO's institutional relationships, data collection and production protocols, and key personnel.

FAO already tracks many mature STIs in FAOSTAT and similar open access data products it generates. Much of those data originate in censuses or nationally representative surveys done by national governments' statistical offices or ministries. In many LMICs, the World Bank plays a key technical advisory role in such data collection.

There remains much to be done to fill gaps across countries and in addressing sampling and measurement error issues in existing series (e.g. on farmer adoption of improved crop varieties, fertilizer, machinery). Advances in satellite-based remote sensing also create new opportunities to generate low-cost, reasonable current estimates of the diffusion of AFS STI that are visible from space, such as irrigation or renewable energy structures (e.g. solar panel arrays, wind turbines) on agricultural lands.

2. **Tracking and assessing pre-emergent and emergent AFS STI and evidence synthesis:** The most transformational impacts at horizons beyond a decade will almost surely come from STI still at early-to-intermediate readiness stages, not yet fully mature and diffusing at scale through AFS. These are the most methodologically complicated tasks of an ATIO, and necessarily evolve quickly with advances in information science. The Wild Futures project originated at CSIRO and now based at Cornell University has been a pacesetter in tackling pre-emergent AFS STI and their potential impacts (Herrero *et al.*, 2020, 2021), while the evidence synthesis experts at Cornell through Ceres2030 have pioneered the use of ML methods for identifying emergent patterns and evidence gaps in science (Porciello, 2020; Porciello, 2021a; Porciello, 2021b). Some of that work is in partnership with exciting initiatives such as the Innovate Food Systems Solutions (IFSS) portal (https://nutritionconnect.org/ifss) – a multi-institution collaboration led by the CGIAR and GAIN, in partnership with multiple groups, including Cornell, Wageningen and other universities. That community of users is working at innovative ways to reimagine how AFS work and to enable different actors to identify solutions to context-specific challenges and opportunities. Partly this involves identifying and generating expert assessment of prospective STI. But it also involves the development and deployment of tools to help users backcast from desired end states to the present, identifying feasible impact pathways to uptake, scaling and intended outcomes from novel AFS STI. The fuzzy boundary between pre-emergent and emergent STI – and the absence of established data collection systems for either of those STI

life cycle stages – favours combining those into a single activity, drawing on the methods and data outlined in sections 6 and 7.

A world-leading research partner could be envisioned as supporting FAO in this endeavour. This is also the space where engagement with the private sector and civil society is both most feasible and most valuable. Private sector investment in AFS STI is growing rapidly and focuses heavily on the pre-emergent and emergent stages. Likewise, many social, policy and institutional innovations originate with civil society organizations (e.g. farmer or community groups). Traditionally, much private AFS STI investment was embodied in new animal and plant genetic materials, agrochemicals, machinery, etc. But a rapidly growing share focuses post-harvest, in food processing and manufacturing, in logistics, and especially in retail and food service (Barrett *et al.*, 2022c; AgFunder Network, 2022). Close collaboration with private sector entities – national industry groups, venture capital monitoring services, etc. – will be essential to success in tracking and assessing pre-emergent and emergent AFS STI. This is not traditionally the domain of FAO, CGIAR or other public sector entities and will require more creative and careful work, with a clear focus on pre-competitive issues in which all parties have an incentive to collaborate and share data.

The pre-emergent and emergent STI workflow mapped out earlier integrates directly with evidence synthesis covering *ex ante* and *ex post* impact assessment of AFS STI. Organizations such as CGIAR, Cornell and 3ie bring considerable experience in facilitating both methodological advances and integrated of evidence on impact assessment as applied to AFS.

Thematic events could be coordinated based on an upcoming or recent ATIO theme and organizations with similar interests. There could be, for example, events around each ATIO edition's theme, co-organized with any of several regular events, including the annual FAO Science and Innovation Forum (https://www.fao.org/science-technology-and-innovation/science-innovation-forum/en), CGIAR Science Forum, or the annual meetings of the International Consortium on Applied Bioeconomy Research (https://icabr.net/), or of the US Department of Agriculture's Impact Analyses and Decision Strategies for Agricultural Research multistate research project (https://www.nimss.org/projects/view/mrp/outline/18787).

ATIO might also engage a high-profile scientific publishing partner. A strong ATIO report will necessarily draw on extensive, technical background material that does not go into a final ATIO intended for a non-technical audience. Those background materials often have considerable value within the academic and research community, both for disseminating new knowledge and for inducing participation by top-flight scientists, for whom scientific publications are a key currency. FAO has successfully partnered with scientific publishers in the past, for example by turning collections of background papers into peer-reviewed special issues or sections of leading journals.[23] Similarly, the Ceres2030 project led by Cornell and IFPRI delivered a high-profile collection of papers in the *Nature* journals.[24] Those are typically one-off arrangements, however, not a recurring platform. There could be an arrangement with a leading scientific publisher that would generate a high-quality series of peer-reviewed, open access books or journal special issues or collections that would itself become a central reference series on AFS STI over time, possibly associated with thematic conferences/workshops associated with each ATIO theme, e.g. an open access edited volume of the technical background papers, published by a high prestige scientific publishing partner. There is currently a publishing agreement between FAO and Springer for the contributions made by FAO staff to Springer Nature's Open Access Books.

23 See for example, the October 2013 and January 2021 issues of *Food Policy* on *Food Systems and the Triple Burden of Malnutrition* and *Food Loss and Waste: Evidence for effective policies*, respectively, based on background papers for the *State of Food and Agriculture* report.

24 See https://www.nature.com/collections/dhiggjeagd/ for the full collection of papers or Laborde *et al.* (2020) for a summary.

EGYPT
A street seller sells vegetables in Cairo.

CHAPTER 12
ATIO FREQUENCY AND CONTENT

An ATIO could be a powerful instrument for fostering accelerated AFS transformation if it can capture and influence key audiences.

An ATIO targeted to country-level and multilateral agency senior policymakers and their advisers, as well as to the public, private and philanthropic investors that finance AFS STI R&D, especially in the LMICs, is envisioned. Those audiences need clear, non-technical messages supported by strong scientific evidence, including open access data. **The vision for an ATIO should be to become the central periodical reference and open access data source on how science, technologies and innovations are changing today's agrifood systems and can transform them to become more efficient, inclusive, resilient and sustainable.** ATIO would be used for advocacy – e.g. for more or different forms of AFS R&D investments – and to help guide prioritization by private and public sector entities.

The appeal of a product that provides comprehensive end-to-end life cycle coverage of AFS STI also poses a major challenge. The inventory of existing, suitable datasets that meet the key inclusion criteria set out in sections 5 and 8 is relatively short, and especially lacking on post-farmgate technologies, and financial, institutional and policy innovations. Furthermore, existing datasets focus heavily on the first and final stages – STI inputs and mature STI – with notable gaps surrounding pre-emergent and emergent AFS STI. Accelerating AFS transformation requires paying considerably more attention to these critical intermediate stages, not least of which to help shorten the considerable lags from initial R&D investments to scaling impactful new STI among AFS actors globally.

It is infeasible to cover all pre-emergent and emergent STI domains adequately and rigorously on an annual basis, for reasons sections 6 and 7 highlight. A natural way to make the scope manageable is to publish ATIO on a regular schedule every two years. The STI outlook products from the United States' National Science Foundation, OECD, UNCTAD and UNESCO appear every two to five years. The WIPO Global Innovation Index comes out annually but relies solely on secondary data. After the protocols for ATIO are well established, in time there might be supplemental editions between the regular biennial ones, tackling key ancillary questions in a shorter format. A biennial publication seems an ambitious but feasible target, appropriately favouring quality over speed.

Each ATIO edition will follow a theme, supported by extensive background research. The first such theme, for the inaugural, 2024 ATIO will be AFS STI for small-scale producers, covering also small- and medium-sized enterprises throughout AFS. This theme targets an outcome of pillar 2 of the FAO Science and Innovation Strategy: "*Access to, and use of, inclusive, affordable and context-specific innovations and technologies aiming at achieving sustainable agrifood systems by small-scale producers, family farmers and other agrifood systems actors enhanced*." Small-scale producers rely more on public and philanthropic STI inputs than do large-scale, multinational corporate AFS actors. This ATIO would explore the innovation advantages and disadvantages that accrue due to scale and how stakeholders can most effectively accelerate STI development, adaptation, diffusion and impacts among small-scale producers globally.

ATIO themes for 2026 and beyond might alternate between STI domains – e.g. digital, genetic, mechanical, novel foods, policy – and intended outcomes or impacts – e.g. land and water conservation, food safety, improved nutrition, improving conditions for AFS workers, building resilience to shocks and stressors – or even on broader themes such as AFS STI impact assessment, or foresight and trade-offs in future AFS. The work on STI domains would naturally inform the more integrative editions focused on key target outcomes and impacts.

The second portion of the ATIO would be a rich data appendix featuring not only material specific to that edition's theme, but also a regular set of empirical evidence in country- and/or indicator-specific tables.

The open access data series that underpin each ATIO publication would be continuously available and updated regularly. These data would be a major public good, curation of which requires careful thought. It would make sense to leverage – or at least link to and share data with – existing platforms, such as the Food Systems Dashboard and the IFSS portal.

Some of the most valuable data would come from integrating AFS STI impact assessments. Rigorous impact assessment is costly. ATIO might usefully provide a portal for scoping and systematic reviews, and statistical meta-analysis, of the body of impact evaluation evidence that sheds light on what reliably works, where, and under what conditions. Such data are among the most useful for resource-constrained agencies operating in LMICs. Those data can take various forms, not just statistical evaluations, but also narrative/qualitative assessments. Some of the most impactful assessments will focus on the bundling of different innovations and technologies, a space that has to date not been well covered by formal impact evaluations. ATIO's evidence synthesis activities would be an ongoing activity, not tied specifically to an edition of the ATIO publication.

ATIO would be a major effort, a pathbreaking initiative. A key decision facing FAO and ATIO investors and partners concerns the prioritization and sequencing of efforts to maintain and build out data collection, analysis, curation and dissemination throughout the AFS STI life cycle. ATIO will almost certainly need to advance in stages, focusing first on curating and communicating existing data series and in expanding to cover more of both the post-farmgate value chain and the institutions and policies that define the food environments in which consumers make dietary choices.

Expert opinions divide sharply as to where to focus in building out data collection, analysis and curation. Those in multilateral organizations largely recommend a clear focus on STI inputs, while private sector respondents emphasize that the most essential areas to advance concern the pre-emergent and emergent STI. The ATIO team sees merit in both arguments, but the collection, analysis and curation of reliable data in the pre-emergent and emergent STI spaces likely offer the greatest promise for accelerating AFS transformation, especially in LMICs. The pace of private sector activity, including in LMICs, has picked up substantially in recent years.[25] As private sector AFS STI financing grows rapidly, relative to public investments, it becomes ever more important to engage that community. Their interests lie most firmly in the intermediate stages of pre-emergent and emergent STI. Both because it will facilitate engagement of the private sector – which will be essential to a successful ATIO – and because it would fill an especially big void in the present AFS STI landscape, ATIO will initiate work to improve understanding of the pre-emergent and emergent phases from the inception of ATIO, especially as it relates to LMICs.

The broader ATIO programme, however, should help spark new initiatives to fill AFS data and evidence gaps more broadly and to employ the data and analyses curated and produced by ATIO to inform policymaking. As articulated in the theory of change in section 1, ATIO has the potential to be a powerful driver of investment in data and evidence generation as well as evidence-based policymaking to help accelerate

25 One telling example is that in late March 2022, two African startups – Kenya's Apollo Agriculture and Nigeria's ThriveAgric – raised USD 40 million and USD 56 million, respectively, in new financing in one week (https://agfundernews.com/thriveagric-apollo-ag-score-nearly-100m-in-big-week-for-african-agtech). Agrifood technology firms raised at least USD 52 billion in new investments in 2021, a 75 percent growth over 2020, with the largest deals taking place in emerging markets – China, India and Brazil were three of the top six countries globally in 2021 agrifood-tech investment – and in downstream value chains segments such as food delivery and innovative (e.g. cellular, fermentation, or plant-based) foods (AgFunder Network, 2022).

AFS transformation worldwide, but especially in today's LMICs where it is most essential. It is expected that over time ATIO will induce consortium members and a broader stakeholder ecosystem to convene communities of practice on the tracking and measurement of AFS STI dynamics to reinforce best practices around evidence-based AFS policymaking and investment.

APPENDIX A
DETAILS ON INDICATORS REVIEWED

Using the inclusion criteria detailed in section 5, the structured data reviewed was classified for STI inputs (section 5) and mature STI (section 8) into two groups: prioritized (i.e. satisfy all inclusion criteria) and not prioritized (i.e. do not satisfy one or more inclusion criteria). Those indicators are described in the tables that follow (Tables A1-A4). The database with further details on each indicator – the number of total countries and LMICs covered, the percentage of countries with at least one observation available 2016-present, and notes on the dataset – are available on request.

TABLE A1 SCIENCE, TECHNOLOGY AND INNOVATION INPUTS DATA SERIES PRIORITIZED

Indicator	Subindicator	Definition	Source
R&D Financing			
Government	GERD- Performed by government- Agriculture and Veterinary sciences	Gross domestic expenditure on R&D performed by government in the field of agriculture adn veterinary sciences	UNESCO (United Nations Education, Scientific and Cultural Organization)
Private	GERD- Performed by private non-profit-Agriculture Sciences	GERD stands for "gross domestic R&D capital expenditure". This indicator takes into account the total money financed domestically on R&D in agriculture science by private sector non-profit organizations on a yearly basis.	UNESCO
	Domestic credit to private sector (% of GDP)	Refers to financial resources provided to the private sector by financial corporations, such as through loans, purchases of nonequity securities, and trade credits and other accounts receivable, that establish a claim for repayment. This indicator reflects the ability of private sector contribute to the development of STIs.	World Bank
Higher education	GERD- Performed by Higher Education-Agriculture Sciences	GERD stands for "gross domestic R&D capital expenditure". This indicator takes into account the total money financed domestically on R&D in agriculture sciences by higher education organizations on a yearly basis.	UNESCO

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Indicator	Subindicator	Definition	Source
STI policy environment			
IP regimes	Ratification of UPOV conventions	Mercedes campi database compiles index with yearly scores for the period 1961–2018 for 104 countries, which have legislation on plant variety protection in force. Data include Ratification of UPOV Conventions, Farmer's Exception, Breeder's Exception, Duration and Patent Scope.	Index of intellectual property protection for plant varietes and components, for individual countries, 1961–2018.
	Farmers' exception	This component considers the so-called farmers' right to save seeds, which entitles farmers to use the product of their harvests obtained from a protected plant variety for the purpose of reproduction in their farms.	Index of intellectual property protection for plant varietes and components, for individual countries, 1961–2018.
	Breeders' exception	This component considers the so-called breeders' exception – which states that the exclusion right does not extend to the use of a plant variety for experimental or research purposes by other breeders.	Index of intellectual property protection for plant varietes and components, for individual countries, 1961–2018.
	Protection length	This component considers the duration of the right.	Index of intellectual property protection for plant varietes and components, for individual countries, 1961–2018.
	Patent scope	This component considers whether patents are allowed in five domains which are related to plant breeding and agriculture: (i) food, which processes products from agriculture; (ii) microorganisms, which are closely related to the development of biotechnology and its application to plant breeding; (iii) pharmaceutical products because this industry also relies on biodiversity and genetic resources; (iv) plant and animals – when the invention is not limited to a specific variety; and (v) plant varieties (either sexually or asexually reproduced specific plant varieties). (Definition retrieved from Campi and Nuvolari (2021).	Index of intellectual property protection for plant varietes and components, for individual countries, 1961–2018.
Regulatory capacity	Regulatory Quality Index	Index that reflects perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private-sector development. Scores are standardized.	WIPO Global Innatovation Index (extracted from (http://info.worldbank.org/governance/wgi/#home).
Start-up environment	Enabling the Business of Agriculture	Enabling the Business of Agriculture indicators assess whether governments make it easier or harder for farmers to operate their businesses.	World Bank
R&D physical inputs			
High tech imports	High technology imports	"High-technology imports as a percentage of total trade. High-technology exports and imports contain technical products with a high intensity of R&D, defined by the Eurostat classification, which is based on Standard International Trade Classification (SITC) Revision 4 and the OECD definition. Commodities belong to the following sectors: aerospace; computers and office machines; electronics – telecommunications; pharmacy; scientific instruments; electrical machinery; chemistry; non-electrical machinery; and armament."	WIPO Global Index
Scientific publications	Number of scientific publications on frontier agriculture technology	Number of publications on frontier agriculture technology, reflecting the scientific progress on technology innovation, especially for pre-emegent and emergent STIs.	SCOPUS
Genetic collections	Number of accession per country	This variable is constructed (not sure is valid or not), it represents the crop diversity within a country.	Genesys

TABLE A2 MATURE SCIENCE, TECHNOLOGY AND INNOVATION DATA SERIES PRIORITIZED

Indicator	Subindicator	Definition	Source
Primary production			
Improved seed	GM crop events approved	It features the biotech/GM crop events that have been approved for commercialization/ planting and importation (food and feed).	International Service for the Acquisition of Agri-biotech Applications (ISAAA)
Fertilizers	Agricultural use	Amount used in the agricultural sector in the year. The unit is in tonnes.	FAOstat
	Fertilizers	Total N, P2O5, K2O nutrients from inorganic fertilizers and N from organic fertilizers applied to soils, in 1000 metric tons	International agricultural total factor productivity (TFP) indices, 1961–2019
Pesticides	Pesticide use	It includes data on the use of major pesticide groups (Insecticides, Herbicides, Fungicides, Plant growth regulators and Rodenticides) and of relevant chemical families. Data report the quantities (in tonnes of active ingredients) of pesticides used in or sold to the agricultural sector for crops and seeds.	FAOstat
Tillage	Cropland area under conservation tillage	Cropland area (in 1000 ha) on which tillage practices leave plant residues (at least 30–35 percent) on the soil surface for erosion control and moisture conservation.	UN DATA-FAO
Plant-based/ celluar meat ops and proteins	Alternative protein manufacturers and brands	This data takes scope of all existing alternative protein/plant based food corporations around the world; keeps track of variables such as country of location, operating regions, year founded, and founders.	Good Food Institute
Cultivated land area	Land area equipped for irrigation	The area equipped for irrigation covers areas equipped for fully controlled irrigation by any of the methods of surface, sprinkler or localized irrigation. The equipment does not have to be used during the reference year. It also includes areas under partially controlled irrigation methods of spate irrigation (controlling flood waters to water crops), equipped wetlands and inland valley bottoms and equipped flood recession. It excludes manual watering of plants using buckets, watering cans or other devices.	FAOstat
Aquaculture	Aquaculture production	This indicator represents the cumulative weight in pounds of a fish species caught by fisheries in a given country. (i.e. 5 000 tonnes of salmon – United States).	FAO FishStatJ
Improved animal health/ genetics/ nutrition	Control measures	Type of inspection given to help cure given animal-affecting diseases, in a given country.	World Organisation for Animal Health
Physical investments	Net Capital Stocks	Physical investment in capital stocks for agriculture, forestry and fishing, data are corrected for depreciation	FAO
Total factor productivity	Total factor productivity	It is a ratio of total output index to total input index	International agricultural total factor productivity (TFP) indices, 1961–2019
Post-harvest technologies			
Biodeisel production	Biodeisel production	Thousands of tonnes of oil equivalent biodiesel energy produced. Biodiesel energy is an energy derived from agriculture harvest that can be used as a replacement for diesel.	OECD.Stat

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Indicator	Subindicator	Definition	Source
Supply chain and Infrastructure	Agricultural Infrastructure	The indicator measures the ability to store and transport crops to market, based on assessment of a country's i) investments in crop storage facilities ii) road infrastructure iii) air, port, rail infrastructure, as well as iv) irrigation infrastructure.	Global Food Security Index
Internet access	Individuals using the Internet, total (%)	Percentage of population using the internet on individual basis, considering the spread of new agriculture technology through internet access	ITU
	Households with Internet access at home (%)	Percentage of households with internet access at home, considering the household access to new agriculture technology.	ITU
Processing, manufacturing and packaging			
Fortification regulations	Mandatory fortification	The country has legal documentation that has the effect of currently mandating fortification of the food vehicle in question with one or more vitamins or minerals i.e. the documentation indicates that fortification of all or some of the food is compulsory or required.	Global Fortification Data Exchange
Reformulation regulations	Reformulation of foods and beverages	Number of countries that passed policies in regards to fats, salt/sodium and/or sugars.	Global database on the Implementation of Nutrition Action (GINA)
Labour issues			
Minimum wage laws apply	Minimum wage	Statutory gross monthly minimum wages in US dollars (converted using exchange rates), latest year.	ILOSTAT Statistics on wages
Consumer-facing food environment			
Modern grocery retailers and supermarkets	Modern grocery retailers and supermarkets Per 100 000 population	The number of supermarkets per 100 000 inhabitants. Euromonitor defines supermarkets as "Retail outlets selling groceries with a selling space of between 400 and 2 500 square metres. Excludes discounters, convenience stores and independent grocery stores." Note that for some countries, data is modeled by Euromonitor based on estimates from other countries with similar geographic, sociodemographic, and macroeconomic dimensions. Population was determined using estimates from the World Bank.	Food systems dashboard

TABLE A3 SCIENCE, TECHNOLOGY AND INNOVATION INPUTS DATA SERIES NOT PRIORITIZED

Section	Name	Link
Public R&D financing	ASTI	https://www.asti.cgiar.org/pdf/GlobalAssessmentDataTables.pdf
	INSTePP	
	IFPRI – 2019 Statistics on Public Expenditures for Economic Development (SPEED)	https://doi.org/10.7910/DVN/MKX1TU
	FAO – Government Expenditure on Agriculture	https://www.fao.org/faostat/en/#data/IG
	OECD	https://stats.oecd.org/Index.aspx?DataSetCode=DV_DCD_PPFD
philanthropic	OECD	https://stats.oecd.org/Index.aspx?DataSetCode=DV_DCD_PPFD
	Bill and Melinda Gates Foundation	https://www.gatesfoundation.org/about/committed-grants
	Ford Foundation	https://www.fordfoundation.org/work/our-grants/grants-database/grants-all
	The Rockefeller Foundation	https://www.rockefellerfoundation.org/grants/
higher education	WIPO GII 2021 (extracted from: World Economic Forum, Executive Opinion Survey 2020 (2018–20), Appendix C of The Global Competitiveness Report 2020. (https://www.weforum.org/reports/the-global-competitiveness-report-2020)	https://www.wipo.int/edocs/pubdocs/en/wipo_pub_gii_2021.pdf
R&D personnel	UNESCO – UNESCO Institute for Statistics	http://data.uis.unesco.org/Index.aspx?DataSetCode=SCN_DS&lang=en
	ASTI	https://www.asti.cgiar.org/pdf/GlobalAssessmentDataTables.pdf
	UNESCO	http://data.uis.unesco.org/Index.aspx?DataSetCode=SCN_DS&lang=en
	GFAR – The Global Forum on Agricultural Research and Innovation	https://www.gfar.net/information-gateway
IP regimes	PLUTO Plant Variety Database	https://pluto.upov.int/search
	Global Preferential Trade Agreements Database	https://wits.worldbank.org/gptad/database_search_results.aspx?show=1
startup-environment	World Bank	https://www.doingbusiness.org/en/data
	"WIPO Global Innovation Index (extracted from World Bank, Doing Business 2020, Comparing Business Regulation in 190 Economies.)"	https://www.wipo.int/edocs/pubdocs/en/wipo_pub_gii_2021.pdf
gene collection	The GRIN-Global Project	https://www.grin-global.org/
gene collection	Gramene	https://www.gramene.org/

TABLE A4 MATURE SCIENCE, TECHNOLOGY AND INNOVATION DATA SERIES NOT PRIORITIZED

Section	Name	Link
Primary Production – Pesticides	OECD.Stat	https://stats.oecd.org/Index.aspx?DataSetCode=STAN
Primary Production – reduced tillage	Nature.com Journal	https://www.nature.com/articles/s41597-021-00817-x
Primary Production – % cultivated land irrigated	World Bank Group World Development Indicators	https://data.worldbank.org/indicator/AG.LND.IRIG.AG.ZS?end=2018&start=2001&view=chart
Primary Production – aquaculture	OECD.Stat	https://stats.oecd.org/Index.aspx?DataSetCode=STAN
Primary Production – improved animal health/genetics/nutrition	OECD.Stat	https://stats.oecd.org/Index.aspx?QueryId=77269
Primary Production – # farms/extension agent	International Food Policy Research Center	https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/JEQ9BO
Primary Production – precision ag machinery	Smart agriculture	https://www-statista-com.proxy.library.cornell.edu/study/46794/smart-agriculture/
Primary Production – %cultivated area in cover crops	Cover crop information map	https://gocovercrops.com/
	Permanent cropland (% of land area)	https://data.worldbank.org/indicator/AG.LND.CROP.ZS
	Cover crops database	https://sarep.ucdavis.edu/covercrop
Primary Production – Plant-based proteins	Good Food Institute	https://gfi.org/resource/alternative-protein-company-database/
	Protein Directory	https://proteindirectory.com/alt-protein-database/
	Asia Alt Protein Startup Directory	https://www.greenqueen.com.hk/asia-alt-protein-directory-database/
Primary Production – Power irrigation	FAO Aquastat	https://www.fao.org/aquastat/statistics/query/index.html?lang=en
Primary Production – Energy use	OECD.Stat	https://stats.oecd.org/Index.aspx?DataSetCode=STAN#
Primary Production – Improved water resources & quality	FAO Aquastat	https://www.fao.org/aquastat/statistics/query/index.html?lang=en
Primary Production – Improved water resources & quality	OECD.Stat	https://stats.oecd.org/Index.aspx?DataSetCode=STAN#
Primary Production – Improved soil quality	OECD.Stat	https://stats.oecd.org/Index.aspx?DataSetCode=STAN#
Primary Production – Improved soil quality	FAO Stat	https://www.fao.org/faostat/en/#data/GV
Primary Production – Forestry	UN Data Fao	https://www.fao.org/faostat/en/#data/GV

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Section	Name	Link
Post-harvest technologies – Improved storage bags	Engineering for change – Agricultural Solutions Database	https://www.engineeringforchange.org/solutions/products/?category=agriculture
	OECD	https://stats.oecd.org/Index.aspx?DataSetCode=DV_DCD_PPFD
Processing, manufacturing, and packaging – Reformulation regulations	Best practices of member states in food reformulation	https://ec.europa.eu/health/sites/default/files/nutrition_physical_activity/docs/2016euskpresidency_bestpractices_en.pdf
Processing, manufacturing, and packaging – Transportation	FAO Aquastat	https://www.fao.org/aquastat/statistics/query/index.html?lang=en
Processing, manufacturing, and packaging - Energy-efficienct waste disposal	FAO Stat	https://www.fao.org/faostat/en/#data/RFB
Labor issues – Agriculture labour employment	International agricultural total factor productivity (TFP) indices, 1961–2019	https://www.ers.usda.gov/data-products/international-agricultural-productivity/
Labour issues – Minimum wage laws apply	Global WageIndicator Minimum Wage database	https://wageindicator.org/salary/minimum-wage
	OECD Real Minimum Wage	https://stats.oecd.org/Index.aspx?DataSetCode=RMW
Consumer-facing food environment – Electronic food assistance	World Bank Group Social Protection Unit	https://www.worldbank.org/content/dam/Worldbank/Event/social-protection/Gentilini%20-%20Food%20assistance%20as%20a%20safety%20net.pdf
	Digital Food Lab	https://www.digitalfoodlab.com/en/foodtech-database/
Consumer-facing food environment – Cashless retail	World Bank G20 Financial Inclusion Indicators	https://databank.worldbank.org/source/g20-financial-inclusion-indicators/Series/GPSS_2

APPENDIX B
POTENTIAL SOURCES OF INFORMATION FOR AGRIFOOD SYSTEMS START-UPS

Database inventories of start-ups

A range of start-up databases exists to assist in compiling a list of agrifood start-ups. The accessibility of these databases varies, many offer user registration free of charge. Once registered, the ease of accessing data can vary substantially. For instance, the Agrifood Cooperative Platform does not require a log-in, upon opening the webpage allows for filtering by country, organization type, type of organization within agrifood, services provided, as well as agriculture and food production type, then the results are shown on a map providing organization details and links to the individual websites (Innovation Technology Cluster, n.d.). It houses just under 1 000 different agrifood organizations. In contrast, CompassList is a website that requires setting up a free log-in but houses more than 7 000 start-ups (CompassList, n.d.). The site allows for filtering by country, HQ, funding stage, sector, technology and company status. Within the funding stage, the primary focus for finding innovative technologies would be on bootstrap/pre-seed and angel/seed, with the potential for some interest in Series A. Within the sector category, there are numerous options that fall within agrifood, such as aquaculture, alternative protein, agriculture and fishery, urban farming, food tech, circular economy, etc. The focus of the databases is heterogeneous, with some databases focusing on early-stage start-ups, whereas others can have broader coverage in terms of firm maturity. Another robust database of innovations is the Global Innovation Exchange which houses over 7 000 global development related innovations in an open source downloadable excel (Global Innovation Exchange, n.d.). The format includes countries implemented, lives impacted, updated dated, incubated within, one-liner, URLs, stage and many other fields. While the Excel version of the inventory remains available, as of autumn 2021 it will no longer be updated due to lack of funding.

Databases of funders supporting agrifood system start-ups

There is a great diversity of potential funding sources that can be explored to build a list of agrifood start-ups. To help categorize sources, groups within the broader category of innovation platforms were created (Table B1).

Portfolios of early-stage investment firms can identify newer innovations, and the funding round can designate the maturity of the innovation. For example, the different funding rounds are often labelled pre-seed, seed, series A. Firms commonly make a list of their portfolios publicly available on their company website (Table 3).

For the purposes of this paper, an investor is defined as a person or organization (typically a firm) that provides funds to other organizations to help that organization grow and with the expectation of receiving a financial return. A strong emphasis was placed on firms rather than individuals. Viewing investor databases can provide lists of investors that can lead to their portfolios. Alternatively, some platforms consist of both start-ups and funders with the intention to connect the two. For instance, some of the more known platforms in this area are CrunchBase (https://www.crunchbase.com/hub/startups-founded-in-2021), TechCrunch (https://techcrunch.com/startups/), Pitchbook (https://pitchbook.com/solutions/startups), Plug and Play (https://www.plugandplaytechcenter.com/startups/our-startups/), Deal Room (https://app.dealroom.co/companies.startups), and CB Insights

TABLE B1 CLASSIFICATION OF REVIEWED START-UP FUNDING SOURCES

Innovation platforms	**Start-up DB**	Platforms or databases created with the primary purpose of listing start-up organizations
	Investors	Organizations or individuals looking to provide funding to growing organizations with the intention of generating a return
	Investor DB	Platforms created as lists of active investors or for the purpose of connecting investors and investees
	Open Calls/Award/ Challenges	Opportunities for innovators to share their ideas usually in the hopes of creating attention and support
	Accelerator/Incubator	Programmes designed to help organizations looking to grow to continue to thrive
	Foundation	Non-profit organization created by an individual or group of donors, established to provide funding to organizations and non-profits
-	**Grant DB**	Database created to catalogue grant opportunities and sometimes connect granters to grantees
	Crowdsourcing	Platforms that create access to the general public to invest in organizations
	Ecosystems	Platforms intended to create a network around a commonality to build and access knowledge

(https://www.cbinsights.com/). These are all general investment platforms, but as the most well-known, they are more commonly used and have robust inventories of start-ups. In addition, there are resources that have been putting together airtable lists (so they can be continuously updated), some of which can be exported into CSV files and others cannot. For instance, Foodhack has a list of more than one hundred investors that are actively investing in food technology (Foodhack, n.d.), while there is another list of the names, website details and such of over 215 early-stage venture capitalist funds available to download into a CSV file (Goldman, n.d.). Utilizing these lists to get to the venture capital portfolios typically shared on their website can provide insight into early-stage organizations that investors believe have high potential (see Table B2).

Another robust source of early agrifood companies is in open calls, laboratories, challenges or awards. Often funders looking for innovative ideas will launch open calls requesting applicants to help solve specific or broad problems. These sources can help to find some of the newest ideas. Some platforms share all submissions publicly or directly with other applicants. These are databases of not only the winners but all submissions and can be a way to find early-stage organizations that may not yet have received investment.

For example, Agrifood Game Changers Lab is a collaboration between EAT, IDEO, Thought For Food, The Rockefeller Foundation, Forum for the Future, Meridian Institute, SecondMuse and Intention 2 Impact, which gives access to all submissions and creates 24 teams of innovators with similar targeted focuses to work on innovative solutions (de Haas, 2021). The team categories span from upcycling food and materials to reducing food waste to innovating packaging to improving soil health. At other times open calls will release a list of the top ideas and the winners. The Entrepreneurs World Cup (https://platform.entrepreneurshipworldcup.com/display/IN/2021+EWC+100) posts the top 100 innovations from their annual competition. Open calls often occur at regular frequencies annually, biannually, or quarterly, providing the opportunity for comparison over time. Awards and challenges are also often given out as an incentive to attract innovative ideas with the promise of recognition and prizes for the winners. For example, UpLink has a challenges platform where they post challenges on topics like Blue Carbon, Global Climate Shapers, and Circular Economy (The World Economic Forum, n.d.). The UpLink Challenges Platform provides access to the contributions submitted as well as the top innovations. MIT hosts the Sustainable Food Systems Challenge and posted seven winners,

TABLE B2 DEFINING EARLY FUNDING ROUNDS

Early funding rounds	Definition
Bootstrap or Pre-seed	▸ Minimally viable product ▸ Market identified ▸ Path to market
Seed or Angel	▸ Starts to sell product ▸ Quality team assembled to build the company
Series A	▸ Established market fit ▸ Growing sales ▸ Potential to continue to grow sales

eight additional finalists, and 250+ submissions (MIT, 2021). Another option is a potential collaboration with a platform that does not release all submissions publicly but has a dataset of innovations.

Other resources for start-ups that also occur at regular frequencies tend to be offered by accelerators, incubators, and foundations. There are regular cohorts formed for each that choose the most promising organizations that align with the specialty area of that accelerator, incubator or foundation. Examples of fellowships would include Skoll Foundation (https://skoll.org/community/emerging-leaders-initiative/), Mulago Foundation (https://www.mulagofoundation.org/henry-arnhold-fellows), Acumen (https://acumen.org/fellowships/), EIT Food (https://eit.europa.eu/our-activities/opportunities/eit-food-ris-fellowships-2021), among many others. According to data from International Business Innovation Association reported by Forbes in 2019, there were approximately 7 000 business accelerator programmes and incubators (Cremades, 2019). These can be narrowed down by specific industries or stages of development, but it is an extensive list. It is common for accelerators, incubators, and foundations to post their portfolios on their websites. These are common across the globe some are targeted globally like YCombinator (https://www.ycombinator.com/) and others are region or category specific like GROW Accelerator (https://www.gogrow.co/), which focuses on agrifood businesses in Southeast Asia.

Several grant management platforms also exist to match donors with applicants. While these resources contain several non-profit organizations, there is also a growing number of social enterprises with innovative technologies also seeking grant opportunities. There is some diversity across the platforms it is common to require a log-in, while some are free others offer free trials before requiring payment. The United Nations catalogues their grants in a platform that also allows one to apply for the grant on it (United Nations, n.d.). In contrast Fluxx was created for non-profits and is free to use while Instrumental offers a 14-day trial before requiring a user or organization to pay (Fluxx Grantseeker, n.d.). Some have downloadable formats which make for simpler data use.

The earliest stage start-ups are usually funded by founders, family, and friends (Spiegel *et al.*, 2016, 421–449). This means that they will be more challenging to locate because the organizations will not be available from funding sources. However, built on the premise of getting family and friends to invest and making funding more accessible, numerous crowdfunding organizations are now available. Crowdfunding sites have emerged as a way to launch a company, gain early clients and brand awareness, and have made investing more accessible to the average person. With time, crowdfunding has evolved into numerous models, the primary one explored here is equity crowdfunding. However, there are many sites that also aim to provide transparency into donations and provide access to marginalized communities that might not otherwise have access to funding. As such, crowdfunding websites are good places to find a collection of new innovative organizations that have community buy-in. There are general international crowdfunding platforms like GoFundMe (https://www.gofundme.com/) Kickstarter (https://www.kickstarter.com/), Indiegogo (https://www.indiegogo.

com/), Crowdfunder (https://www.crowdfunder.co.uk/), Wefunder (https://wefunder.com/), Angellist Venture (https://www.angellist.com/), etc. While other sites are more specialized some are more geared towards early-stage funding such as Crowdcube (https://www.crowdcube.com/), Seedrs (https://www.seedrs.com/), OurCrowd (https://www.ourcrowd.com/), Fundify (https://fundify.com/), Funding Societies (https://fundingsocieties.com/), and others. Other platforms are specifically geared towards agrifood companies like FoodHack (https://foodhack.global/), Vegan Launch (https://veganlaunch.com/), and Sustainable Food Ventures (https://www.sustainablefoodventures.com/). There are also regional focuses to accommodate different laws and regulations.

Crowdfunding – a financial innovation that generates resources for STI, among other uses – is seeing tremendous growth globally, and not only in the high-income countries (Box E). For instance, the African Crowdfunding Association is working to make crowdfunding across Africa more transparent and in line with what they identify as "best practices" (African Crowdfunding Association, n.d.). The ACfA has compiled a list of crowdfunding platforms working in Africa that need to abide by these regulations (African Crowdfunding Association, n.d.). Across Asia crowdfunding has been growing in popularity as individual governments have passed legislation on peer-to-peer lending. Growth has also been extensive in Latin America. For example, Brazil saw a growth in funding raised on crowdfunding platforms from USD 8.3 million in 2016 to USD 78.8 million in 2019 (Nery, 2020).

Additional resources are ecosystems, which are platforms intended to create a network around a particular commonality (such as agrifood) for individuals to use to build knowledge and access. The intention is to house as much information in one place as possible. One example would be the Aspen Network of Development Entrepreneurs (ANDE). ANDE is a global network with regional offices that requires paid membership to access investors, experts, trainings and like-minded start-ups (ANDE, n.d.). Another example is the Feed 9 B innovation platform, which is focused on encouraging collaboration and innovation across Asia's food ecosystem (Feed 9 B, n.d.).

Emerging technologies are not limited to new companies but are also often found within big companies that have the means to conduct R&D work. Going directly to the source of these organizations and reviewing their annual reports can help provide some colour to the emerging innovative technologies. Reviewing these documents can require considerable combing as they are often full of information of varying degrees of usefulness and only share non-proprietary knowledge. It is noteworthy that organizations control the narrative for which information is shared. However, looking at their newest product releases or trials can help to indicate their latest innovations. For instance, ADM has 55 different innovation centres, exemplifying the extensive and diverse research being conducted (Archer Daniels Midland Company, 2020). Another aspect is to look at the trends published by major corporations in their own media outlets, although some things may be conducted more secretively, in which case it is important to review IP databases. Looking at the acquisitions and spinoffs can also be a valuable insight into emerging technologies, though they are often further along in the readiness and development scale.

APPENDIX C
STRUCTURED EXPERT ELICITATION METHODS

Reviewing best practices in expert elicitation

Several critical variables of the survey design and workflow need to be addressed when designing the ATIO expert elicitation model. Researchers must determine:

- Which type of elicitation method will be applied.
- Who will be selected to participate.
- What the criteria to define an "experts" will be.
- If all expert answers will be weighted equally or proportionally to their level of expertise.
- What the minimum number of experts required per survey is.
- Will experts be divided into subsets (panels) or surveyed as a whole.
- Which protocols and best practices will be adopted.

"A Practice Guide to Structured Expert Elicitation Using The IDEA Protocol" (Hemming *et al.*, 2017) is a notable guide to the best practice protocols for expert elicitation. The article was influential in shaping the ATIO expert elicitation method. IDEA protocols were chosen to structure the ATIO expert elicitation because they have been well researched and overcome the primary disadvantages of Delphi method expert elicitation. IDEA protocols allow researchers to exponentially decrease the time, money, and resources necessary to complete an expert elicitation. The model has been widely adopted by expert elicitation specialists. Table C1 summarizes the IDEA protocols along with several other common expert elicitation approaches.

Strawman proposal of expert elicitation for pre-emergence technologies

Box C1 offers an example of the workflow designed for the ATIO expert elicitation process. The entirety of the ATIO expert elicitation is done remotely via an online survey platform. Following the inception meeting, all steps of the survey are performed asynchronously. Each survey for each expert panel is implemented in parallel.

Below is a brief description of each stage of the proposed ATIO Expert Elicitation process.

1. **Invitation.** Invitations will be sent prior to the Inception Meeting via email. Invitations will contain plain language that summarizes the purpose, timeline, and contact information of the ATIO research and report. Invitees will be notified that their participation is voluntary and have a right to leave the study at any time. The invitation will also contain a detailed ethics disclosure explaining topics such as protection of anonymity, the use of codenames and encrypting data.
2. **Inception meeting.** The inception meeting is an introductory meeting for the experts who have been invited to participate in the survey. Its purpose is to explain the context and methods of the elicitation. Special consideration should be made to facilitate meetings across multiple languages, and where possible should be a live remote event to maximize participant engagement and increase the likelihood that participants understand the purpose of the elicitation (McBride *et al.*, 2012, as cited in Hemming *et al.*, 2017). The inception meeting should occur at least two weeks before the first round of the elicitation (Hemming *et al.*, 2017).

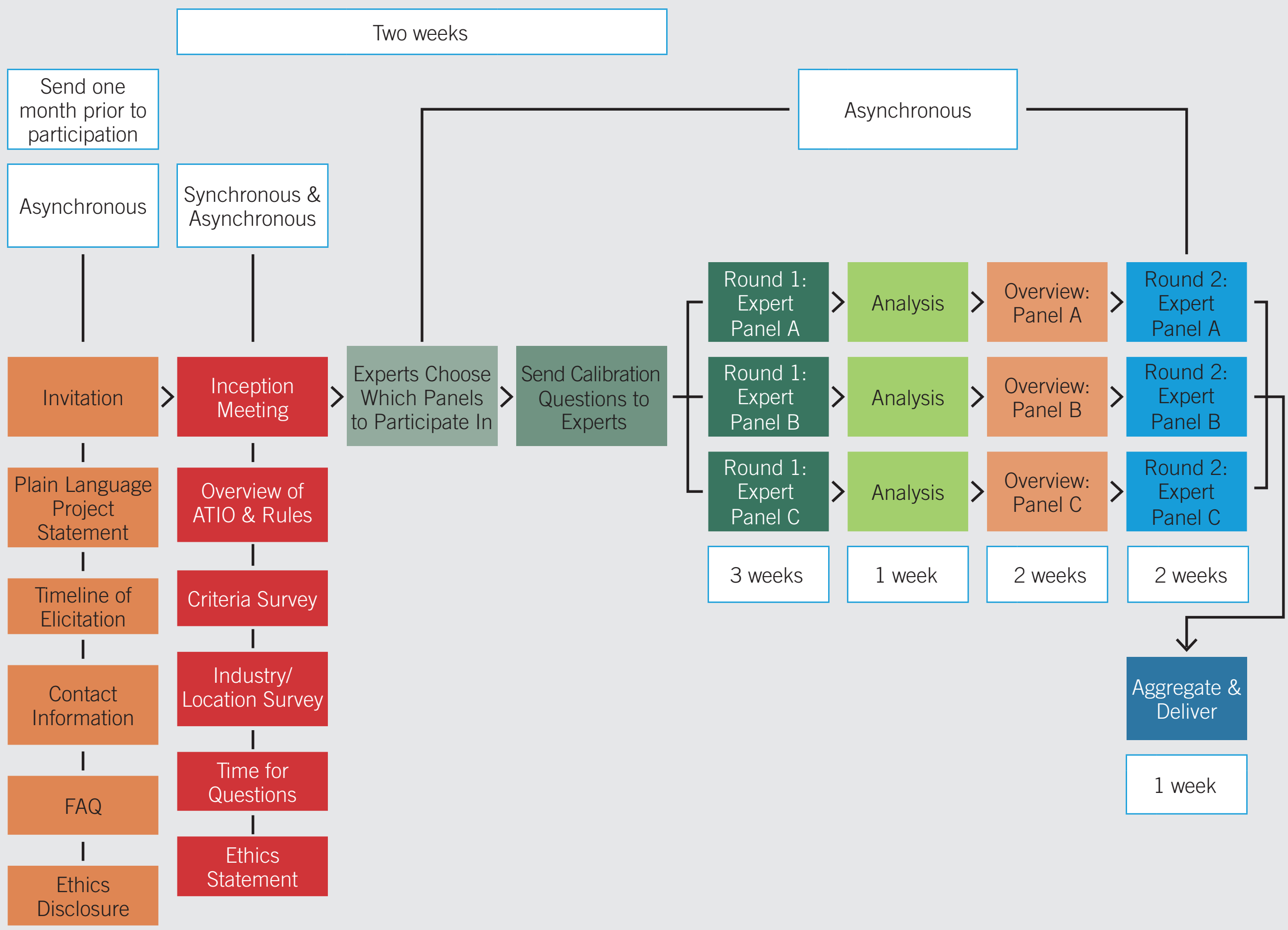
TABLE C1 TYPES OF ELICITATION

	Description
Traditional Delphi Method	Experts are solicited in a multiple round survey (three or more) and unbiasedly steered by a facilitator to come to a group consensus on survey answers. Classically, a Delphi elicitation is in-person, very time consuming for all parties involved, and costly.
Modified Delphi	Similar process as traditional Delphi but various restructurings in the workflow; usually with the intention to reduce the participants' survey time and costs of surveys. Many modified Delphi elicitation designs have two rounds, but there is no standard format. Modified Delphi elicitation methods have allowed researchers to include more experts in the elicitation and have made remote expert elicitation more practical. Modified Delphi models are used by agencies like WHO and NASA.
IDEA Protocols	IDEA protocols are a well-researched set of best practices for expert elicitation methods. There are two primary IDEA models: 3-Step and 4-Step questions. 3-Step is only used for eliciting single event probabilities. It is used to "estimate numerical quantities or probabilities – to obtain approximations of facts that can be cross-examined and used to inform decisions and models (Morgan, 2014, as cited in Hemming *et al.*, 2017)". 3-Steps refer to each survey question having 3 estimates: (1) lowest plausible probability, (2) highest plausible probability, (3) best estimate for probability. Alternatively, the 4-Step approach can be used to estimate predicted quantities and frequencies of events: (1) lowest plausible value, (2) highest plausible value, (3) best guess of the value, and (4) a rating of the confidence level of estimates (between 50–100% confidence) IDEA expert elicitations have a similar design as modified Delphi but do not need to be geared towards the outcome of producing a majority consensus (Speirs-Bridge *et al.*, 2010 as cited in Hemming *et al.*, 2017).
Cooke Method (Weighted Answers)	Rather than weighting all expert opinions equally (classic approach), a method is created to determine the level of expertise for each expert and their answers are weighted accordingly. Experts are given a quiz prior to the first round of the survey to determine the "weight" of their answer when aggregating data. Cooke's Method has shown to be helpful in distinguishing between experts with strength in theory and experts with high degrees of field experiences and applied knowledge (Aspinall, 2010). Depending on the stage of the expert elicitation, it may be important to weight experts.

   a. The meeting will explain that the participants are allowed to "source and discuss information from anyone outside the group" but are not allowed to "discuss the content with each other outside the elicitation" to decrease the challenges and limitations of expert elicitations (i.e. groupthink).
   b. Experts can then ask clarifying questions, and the meeting facilitators will preview the types of questions (i.e. multiple-choice, matrixes) and how to answer them.
   c. Q&A answers at the end of inception meeting should be documented and made available to experts to view at any time during the survey.

3. **Expert elicitation Round 1.** Round 1 will be delivered to experts via a URL link in an online-survey format. Round 1 will be an asynchronous stage. Experts will be given three weeks to complete Round 1 or the survey. The round will include instructions and give experts the opportunity to create a non-identifiable username. Experts can ask clarifying questions at any point during the three-week period. Links will be provided to an FAQ page attached to the expert elicitation research portal (Hemmings *et al.*, 2017).
4. **Analysis and feedback.** Researchers will take one week to clean data from Round 1, standardize data, aggregate estimates, create visual graphics of data and summary tables, and create a feedback document where comments can be added to any part of the document (Hemmings *et al.*, 2017).
5. **Overview.** The overview stage will be an asynchronous event. Over the course of two weeks, experts can view all data collected from Round 1 (all answers being displayed anonymously). The researcher will also create a screen video recording where they will do a brief overview of the results of Round 1, highlighting contrasting views, and posing thought-provoking questions. They will also clarify or re-define any terms used on the survey or results if necessary (Hemmings *et al.*, 2017).

BOX C1 EXAMPLE OF POTENTIAL EXPERT ELICITATION WORKFLOW



6. **Expert elicitation Round 2.** Experts will have two weeks to comment on any section of the data, modify their original answers, or elaborate on their own answers. They can also reply to other experts' comments or elaborate on other experts' answers. Reminders will be sent to experts three days before Round 2 starts and three days before the deadline (Hemmings *et al.*, 2017).

7. **Aggregate.** All data will be checked for mistakes, standard confidence intervals generated, data aggregated, and final estimates will be turned into graphs, tables, and comments. Data will be uploaded into the ATIO expert elicitation research portal for all experts to view and sign off on (Hemmings *et al.*, 2017). This step will take approximately one week, depending on the size of the pool of experts and number of panels created. More time will be required to aggregate and present the cross-comparison of all ATIO expert panels.

APPENDIX D
EMERGENT STIs

As discussed earlier, the first step in NLP based indicator development for emergent STIs is to identify data sources and establish clear targets for each source. The targets should align with overall project vision or final data analysis to reduce the noise in the data. Second, the data are brought into a general storage and processing database via an API or a custom web-scraping code using a web server application. The data undergo a pre-processing stage to evaluate the structure (for data brought into via APIs) and general data cleaning before going into an enrichment pipeline. The enrichment pipeline begins the AI process. The models for this project have been optimized to perform classification and information extraction only, using both unsupervised methods and semi-supervised methods. The modelling process is described in more detail below. The information extraction and classification process is complete once a series of labels are applied to the data.

Results

Step One: Topic modelling

Topic modelling based on Latent Dirichlet Allocation (LDA), Latent Semantic Analysis (LSA/pSLA) and Non-negative Matrix Factorization (NMF) have long histories in analysis semantics of datasets (Jelodar *et al.*, 2019). These models include features such as synonymy—to find relationships between words when different words describe the same idea—and polysemy, where the same word describes different ideas. There are several steps involved in topic extraction, including pre-processing (text normalization, lemmatization and phrase extraction), vectorization (TF-IDF) and removal of stop words (and, the, thereof), before constructing a topic model using approaches such as NMF.

Topic extraction is primarily an unsupervised process in machine learning, which means that there is no human input other than data input and statistical code. Topic modelling is gauged using hyperparameters, or a value that can be used to control the machine-learning process. There is no gold standard to compare against because its interpretability remains unmeasured, instead coherence metrics are used to determine how the model performs. Coherence metrics are calculated as the average/median of the pairwise word-similarity scores of the words in the topic (e.g. PMI). The higher coherence, the better the topic modelling performed (Röder *et. al.*, 2015). Several models for different topic numbers were built and evaluated using a coherence metric to establish that 20 topics provided the highest coherence scores.

Figure D1 shows the same 20 topics by number of documents published each month in 2021. This can provide more information about annual trends and how trends perform in comparison with each other. Finally, Figure D2 shows topic weight distribution is calculated by the number of documents per topic weight, providing another opportunity to compare topic performance within the corpus.

Figure D3 displays the topic weight distribution, which is calculated by the number of documents per topic weight. This provides an insight into how many documents are associated with the three-word strings, offering another data point to evaluate the accuracy of topic modelling.

FIGURE D1 TOPICS DISCOVERED FOR PATENTS DATA

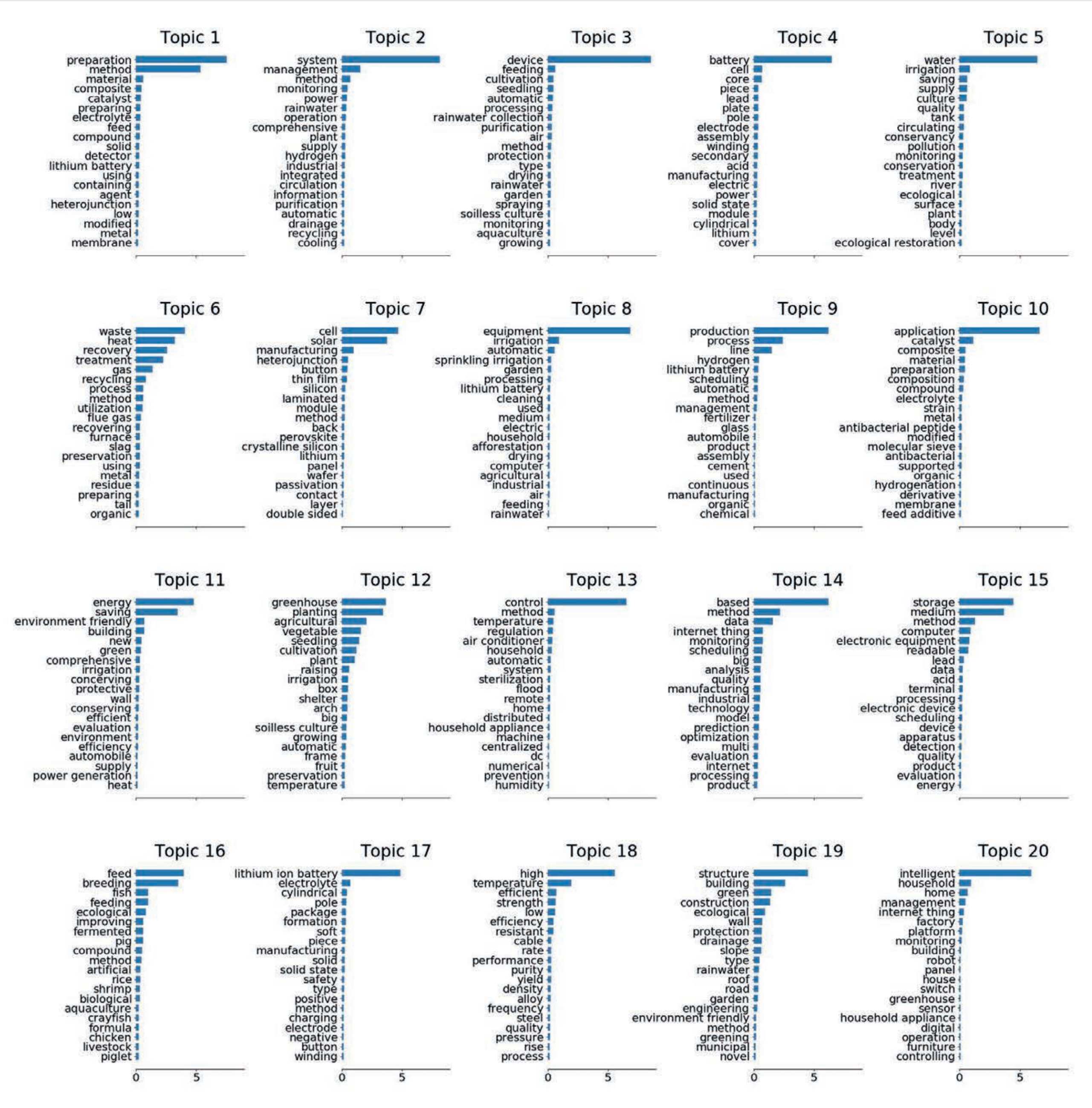


FIGURE D2 NUMBERS OF DOCUMENTS PER TOPIC, PER MONTH, FOR 2021

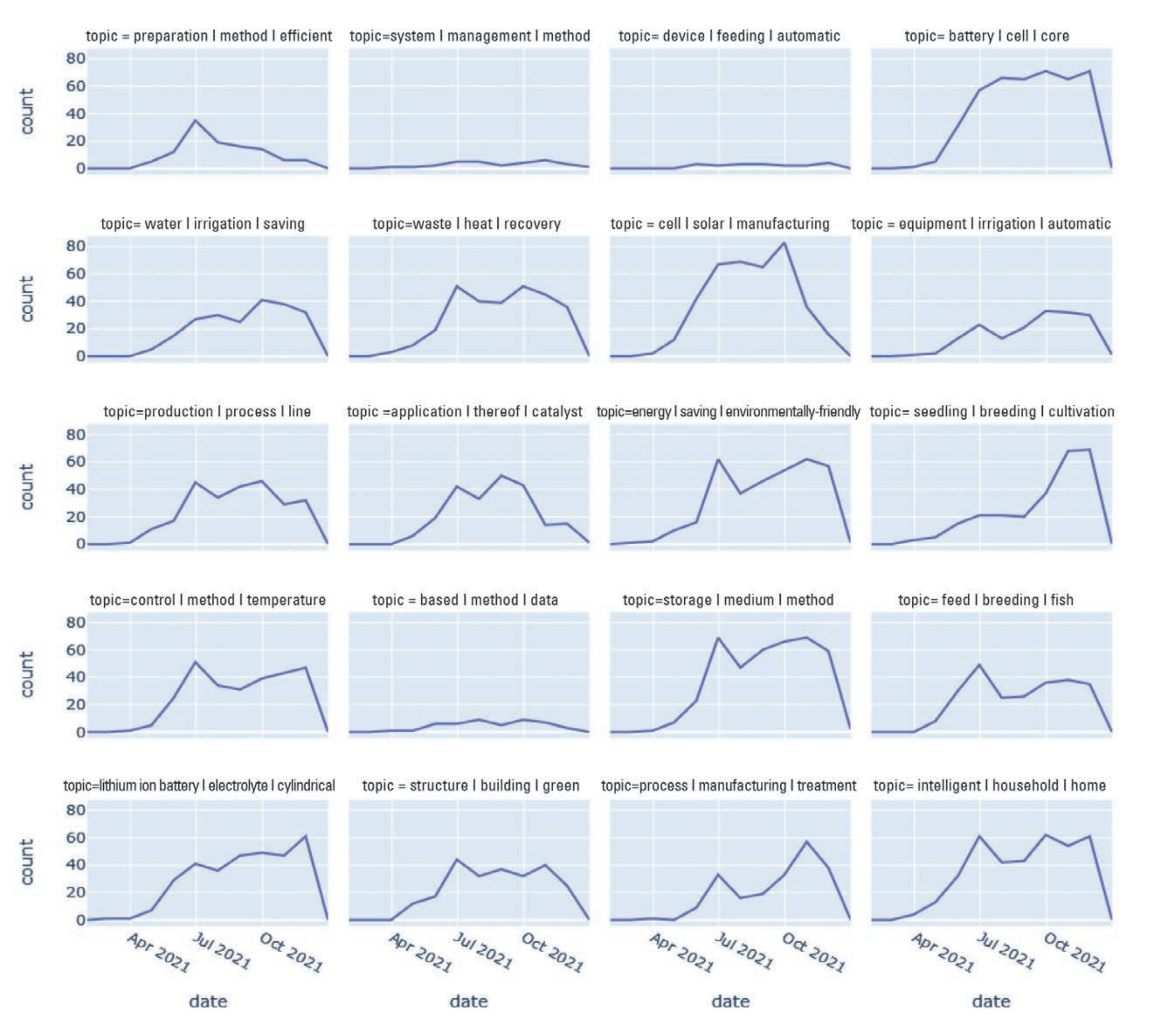


FIGURE D3 TOPIC WEIGHT DISTRIBUTION

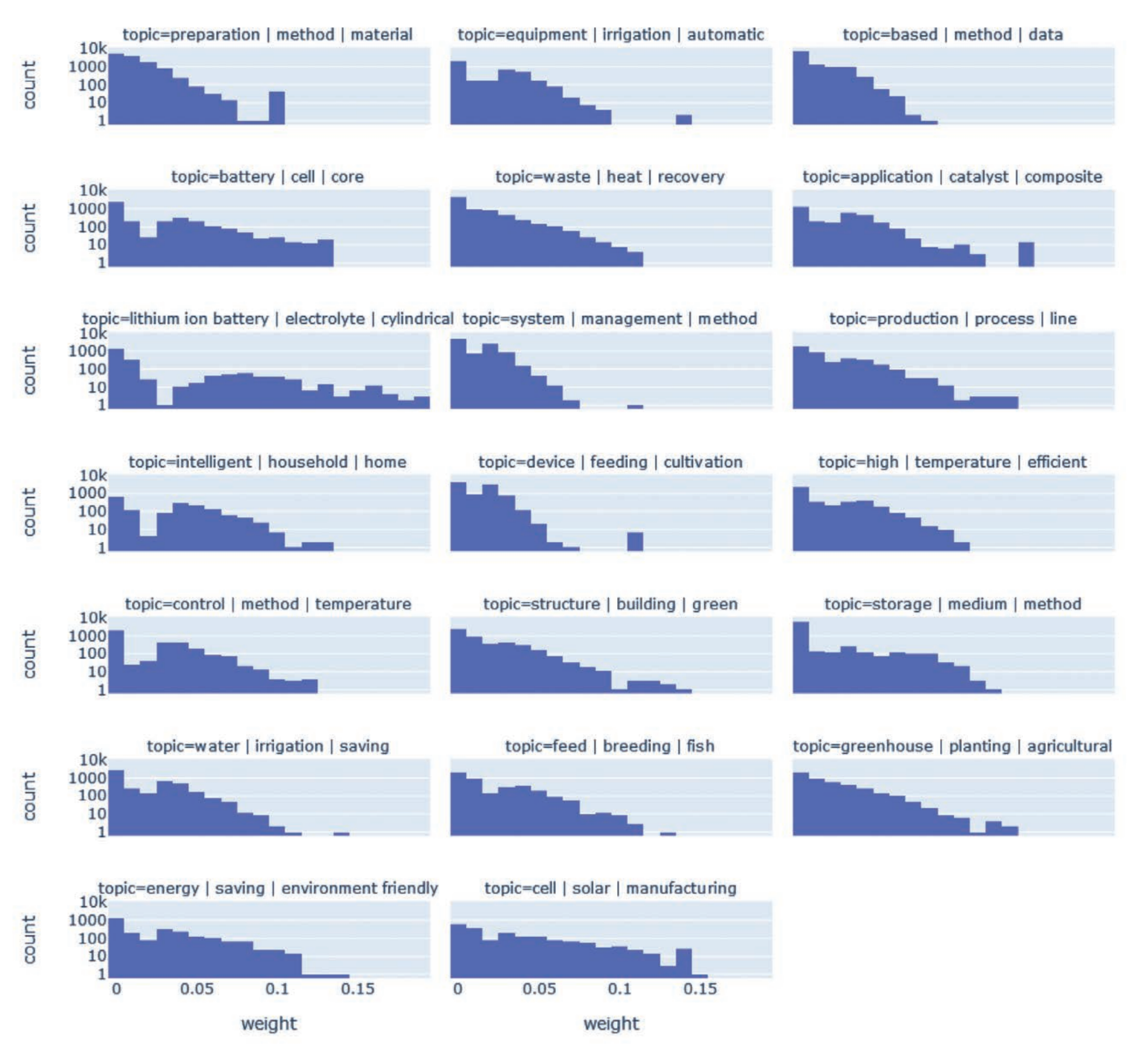


FIGURE D4 CORRELATION BETWEEN INTERVENTIONS FOUND AND IDENTIFIED TOPICS.

Correlation between interventions found and identified topics. The identified topics are presented as word strings, whereas the interventions found_raw and interventions found_extracted are presented as correlations between topics and interventions, calculated between 0 and 1. The higher the value, such a 0.25 in "seeding, breeding, and cultivation" indicates a higher likelihood of specific, relevant interventions

Simple Topic Models	Interventions Found	Interventions Extracted
Feed|Breeding|Fish	0.012	0.026
Lithium ion battery|Electrolyte| Cyclindrical	0.065	0.079
High| Temperature| Efficient	0.003	0.007
Structure | Building | Green	0.078	0.041
Preparation| Method| Thereof	0.165	0.105
System| Management| Method	0.061	0.089
Device | Feeding | Automatic	0.029	0.062
Battery| Cell| Core	0.008	0
Water | Irrigation | Saving	0.052	0.065
Waste| Heat | Recovery	0.076	0.066
Equipment | Irrigation| Automatic	0.047	0.045
Cell| Solar| Manufacturing	0.004	0.025
Production| Line| Automatic	0.068	0.052
Application| Catalyst| Cost	0.088	0.02
Energy| Saving| Environment Friendly	0.03	0.033
Seedling | Breeding| Cultivation	0.254	0.159
Control | Intelligent| Household	0.137	0.113
Based| Method| Data	0.134	0.099
Storage| Medium| Method	0.104	0.056
Greenhouse| Planting| Agricultural	0.186	0.097

Step Two: Emerging STI identification

Transformer models require a semi-supervised learning approach, where human experts review and correct the data at randomized intervals and return the corrected data into the model. The semi-supervised intervention model was combined with the unsupervised topic models to speed up the process to identify emerging technologies. Figure D4 shows the results of combining the intervention extraction model with topic models to identify whether relevant interventions are contained within the topic models. The model extracts interventions from the text in what is termed a "raw label", – shown in the column marked "interventions found_raw" before exploring the model's larger knowledge graph to identify if the intervention, or anything close to the intervention, has been seen by the model before–shown in the column "extracted interventions." There is higher correlation between interventions found and topics, meaning that topic labelling on new data can be used as a preceding step before a more time-consuming and expensive intervention extraction step.

Step Three: Source analysis and information extraction

The final step before analysis is to identify candidates for source review. In the example below (Figure D5), individual patent sources are provided with a coherence metric solely on topic models. In subsequent work, this would feature coherence across raw and extracted interventions, according to step two.

FIGURE D5 INDIVIDUAL PATENT SOURCES AND COHERENCE METRICS BY TOPIC MODELS

id	result link	title	date	preparation | method | material	device | feeding | cultivation	battery | cell | core	water | irrigation | saving	waste | heat | recovery	cell | solar | manufacturing	equipment | irrigation | automatic	production | process | line	application | catalyst | composite	energy | saving | environment friendly	greenhouse | planting | agricultural	control | method | temperature	based | method | data	storage | medium | method	feed | breeding | fish	lithium ion battery | electrolyte | cylindrical	high | temperature | efficient	structure | building | green	intelligent | household | home
CN-11368	https://pa	Method for screening typical problems in complex equipment delivery based on grey target decision	##########	0.00109	0	0	0	0	0	0.02091	0	0	0	0	0	0.02031	0	0	0	0	0	0
CN-11369	https://pa	Zinc phosphate-silane composite passive film modified zinc metal negative electrode and preparation method and application thereof	##########	0.01633	0	0.0025	0	7.4E-05	0	0	0	0.02511	0	0	0	0	0	0	0.00058	0	0	0
CN-11368	https://pa	Phased array weather radar health management system	##########	0	0	0	0	0	0	0	0.00022	0	0	0	0	0	0	0	0	0	0	0.00216
CN-11368	https://pa	Simultaneous multi-channel array processing method based on space-time-frequency code wave technology	##########	0.0004	0.00059	0	0	0	0	0.00048	0	0	0	0	0	0.0264	0	0	0	0.00021	0	0
CN-11368	https://pa	Weighing system for lithium ion battery liquid injection	##########	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.06983	0	0	0
CN-11368	https://pa	Phased array weather radar scanning strategy suitable for civil aviation air traffic control meteorological guarantee	##########	0	0.00023	0	0	0	0	0	0	0	0	0	0.02154	0	0	0	0	0	0	0
CN-11367	https://pa	Intelligent matching method based on type and position of factory equipment	##########	0.00241	0	0	0	0	0	0.03395	0	0	0	0	0	0.03055	0	0	0	0	0.0016	0.04772
CN-11367	https://pa	DCS real-time value setting method and system, equipment and storage medium	##########	0.00021	0	0	0	0	0	0.02853	0	0	0	0	0	0	0.05906	0	0	0	0	0
CN-11367	https://pa	Intelligent matching method for manpower supply and demand based on factory position	##########	0.0019	0	0	0.00324	0	0	0	0	0	0	0	0	0.02792	0	0	0	0	0	0.04252
CN-11368	https://pa	Intelligent fault early warning method and system for textile machinery equipment	##########	0.00449	0	0	0	0	0	0.02924	0	0	0	0	0	0.00145	6.6E-05	0	0	0	0	0.03818
CN-11368	https://pa	Supply chain management method and system for board e-commerce platform	##########	0.00592	0	0	0	0	0	0	0.00095	0	0	0	0	0.00203	0.00144	0	0	0	0	0.00271
KR-20210	https://pa	A system for purifying contaminated earth and stone waste for recycling	##########	0	0	0	0	0.02532	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CN-11367	https://pa	Polypropylene infusion bag quality monitoring and analyzing system based on production complete cycle tracking	##########	0	0	0	0.00117	0	0	0	0.0208	0	0	0	0	0.0207	0	0	0	0	0	0
CN-11365	https://pa	Production line batching method, device, equipment and readable storage medium	##########	0	0.01625	0	0	0	0	0.03198	0.04417	0	0	0	0	0	0.07601	0	0	0	0	0
CN-11367	https://pa	Preparation process and application of gel lithium battery	##########	0.02257	0	0	0	0.00063	0	0.00057	0.02039	0.04888	0	0	0	0	0	0	0	0	0	0
CN-11367	https://pa	Lithium battery electrolyte, preparation method thereof and lithium battery	##########	0.03253	0.00017	0.00027	0	0	0	0.00232	0.00511	0	0	0	0	0	0	0	0.01248	0	0.00114	0
CN-11365	https://pa	Assembly yield control method, equipment and computer readable storage medium	##########	0	0	0.00043	0	0	0	0.0323	0	0	0	0	0.03669	0	0.08349	0	0	0.00052	0	0
DE-20202	https://pa	Cave body for aquarium animals	##########	0	0	0	0.00042	0	0	0	0	0	0	0	0	0	0	5.3E-05	0	0	0	0

Sources with greater relevance would be selected for a deeper analysis to extract specific interventions and other parameters. A spreadsheet of results across patents is provided in a supplemental digital file upon request.

Step Four: Online resource review

The data are sorted into an online resource for review, analysis and adjustment. This is an iterative process that requires feedback from across the research team.

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