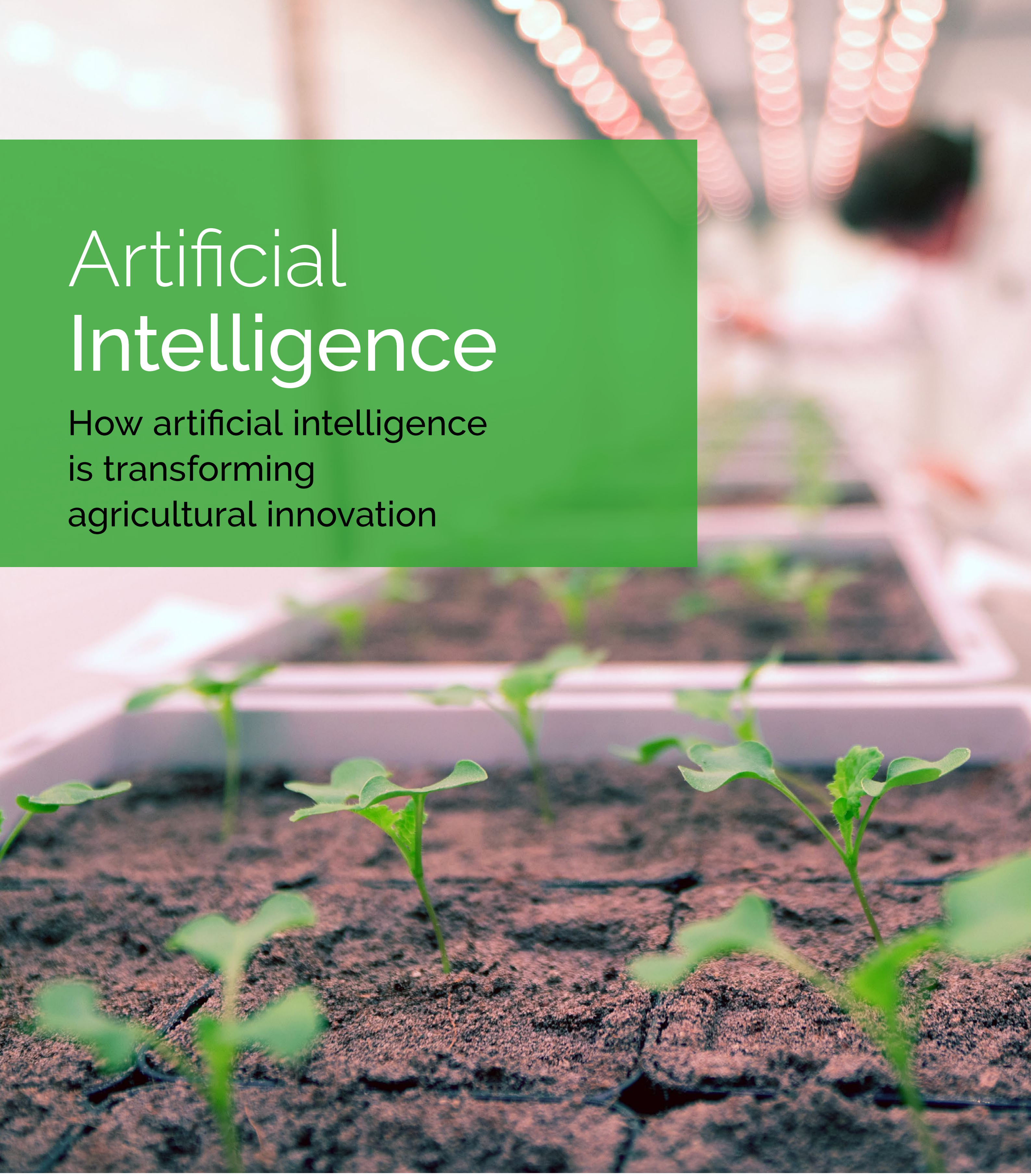
Artificial Intelligence

How artificial intelligence is transforming agricultural innovation



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Acknowledgements

We would like to thank the following for sharing their insights for this report:

- **Alister Campbell**, Vice President, Global Head of Science and Technology, and **Steve Tharp**, President, ELN & Luma, Dotmatics
- **Tonny Otjens**, Group Information Manager, Rijk Zwaan
- **Dr Stephan Köhler**, Principal Scientist for the modelling of active ingredient formulations, BASF
- **Professor Marc Salomon**, Dean and Professor in Decision Science at the University of Amsterdam Business School (ABS) and Director/Founder of the MBA in Artificial Intelligence
- **Dr Marta Dobrowolska-Haywood**, Head of Data Science and Knowledge Management, Croda
- **Dr Finn Bauer**, Vice President of Research and Development for Life Sciences, Croda

Executive summary

Artificial intelligence (AI) is poised to reshape agricultural innovation. This report explores how AI is already being applied across the innovation lifecycle, the technologies underpinning these advances, and the opportunities they create for faster, more targeted and more sustainable product development.

Drawing on insights from experts across agriculture, life sciences and AI, the report examines the organisational changes needed to move from isolated AI projects towards becoming an AI-enabled business. In charting a course, it considers the role of proprietary data, scientific expertise, evolved business processes, trust, and collaboration in creating AI value at scale. It concludes with practical considerations for leaders looking to build organisations that can translate AI into long-term competitive advantage.

Introduction

Imagine a world where every region, perhaps every farm, has access to affordable seeds and treatments tailored to their specific conditions. Even as climates, soil and wildlife ecosystems change, yields continue to rise thanks to wide-ranging interventions that make seeds and crops more efficient and resilient.

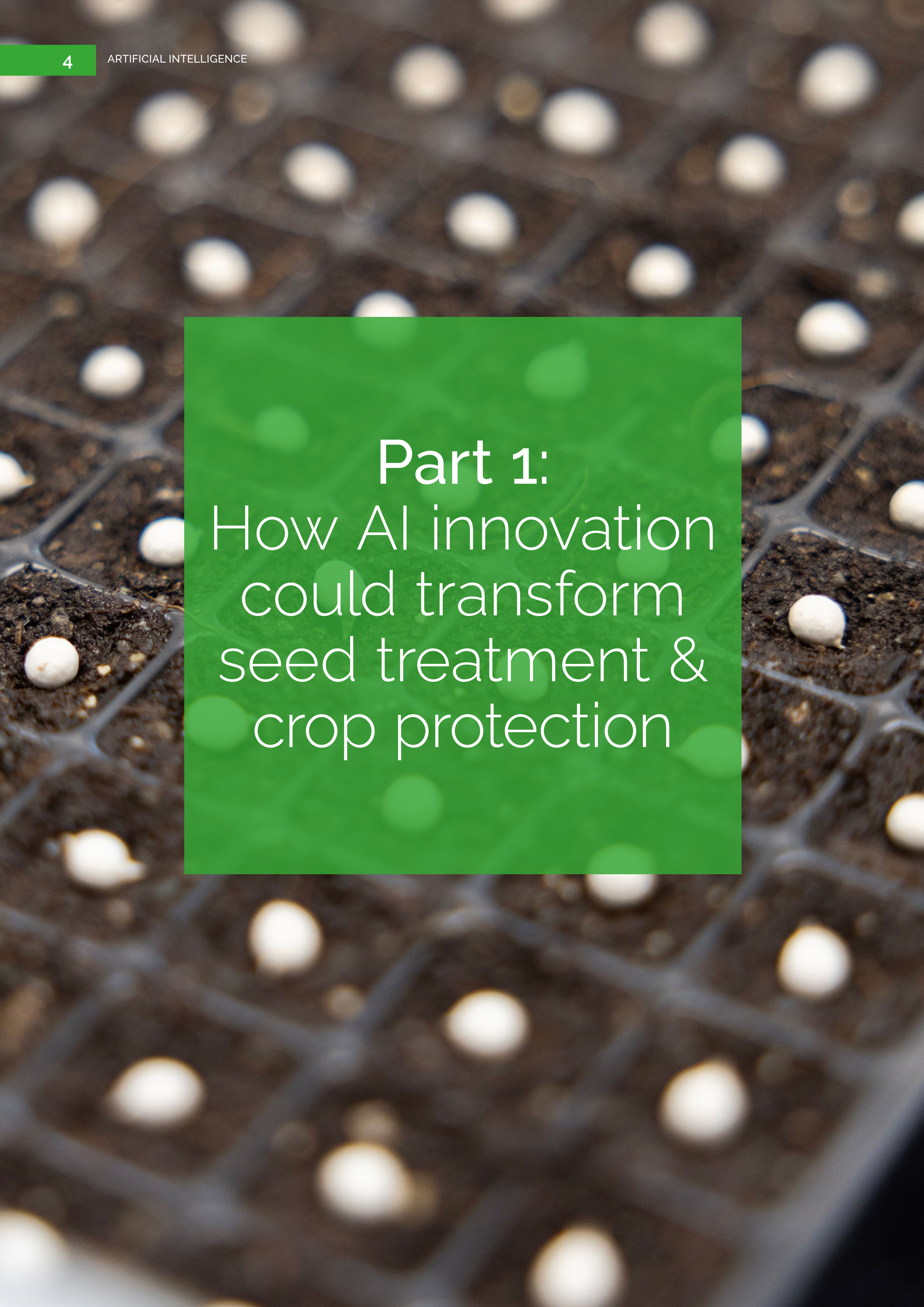
AI is pointing to this possibility, reversing a long-term decline in the rate of new crop protection products being launched. It is helping both breeders and treatment innovators identify efficient routes to more targeted products, some offering ever greater yields, others providing resilience against a wide range of conditions, or helping make agriculture more sustainable.

For farmers, AI may use soil data and weather models to select the right mix of crops and products – from this growing number of targeted options – for their farm, and for the season ahead.

Behind the scenes, the hard work of innovation itself will also be transformed by AI. Scientists are collaborating with AI to generate new ideas, and evaluate their viability before they move to the lab. The administrative burden that once consumed researchers' time – from documentation to regulatory submissions – is being automated away, allowing them to focus on experimentation and problem-solving.

"AI has the potential to shake up an industry whose approach to innovation hasn't changed much for decades, delivering more innovation, faster," says Croda's Finn Bauer. "That could produce improved plants, coatings and treatments that make agriculture more productive, more resilient, and less damaging to ecosystems, even as the world places ever greater strains upon food production systems".

In a volatile world of changing climate and rising food prices, this high potential technology has arrived at an opportune moment. We should not waste it.

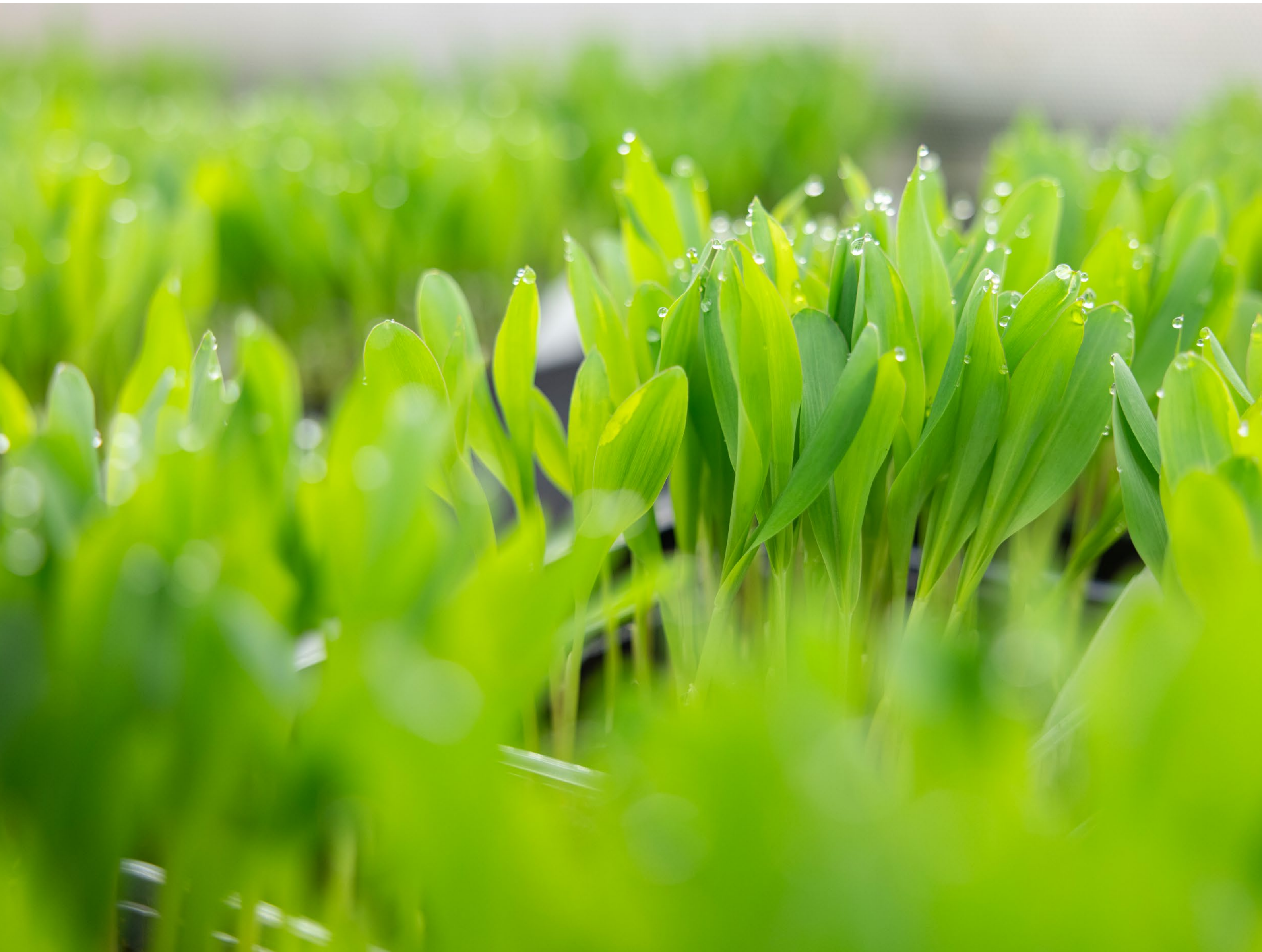


Part 1: How AI innovation could transform seed treatment & crop protection

Changing an expensive, time-consuming and uncertain process

For much of the past century, innovation in areas like crop protection and seed enhancement relied on a familiar formula: observe, test, learn and repeat. Breeders create new plant varieties, scientists develop promising treatments, both are refined through lab and field trials, alongside painstaking analysis. The process has delivered extraordinary advances, but remains expensive, time-consuming and full of uncertainty.

Artificial intelligence – alongside advances in sensing and digital analytics – is changing that equation. “Few things are safe from disruption”, says Marc Salomon of the University of Amsterdam Business School. Yet AI alone will not deliver this future. The organisations that succeed will be those that combine rapidly advancing AI with proprietary scientific knowledge, trusted data and new ways of working.



A wave of new, targeted treatments and protections

At the start of the innovation process, AI is acting as an assistant, and increasingly a research partner. AI can analyse historical research data, scientific literature, and market insights to identify knowledge gaps and generate hypotheses for investigation.

Once ideas spark interest, AI can help researchers predict which genetic combinations, formulations, or treatments are most likely to succeed before testing begins, saving time and reducing dead ends. Life sciences software company Dotmatics described a future in which "dry lab" work – simulation, modelling and prediction – becomes increasingly important before physical experimentation begins.

"There is still a huge level of trial and error," says Tonny Otjens of Rijk Zwaan, a leading fruit and vegetable breeding company. "In future we hope to reduce this drastically by predicting much more in silico."

"If it becomes easy to find the needle in a haystack, then it doesn't matter that it's a haystack."

Tonny Otjens

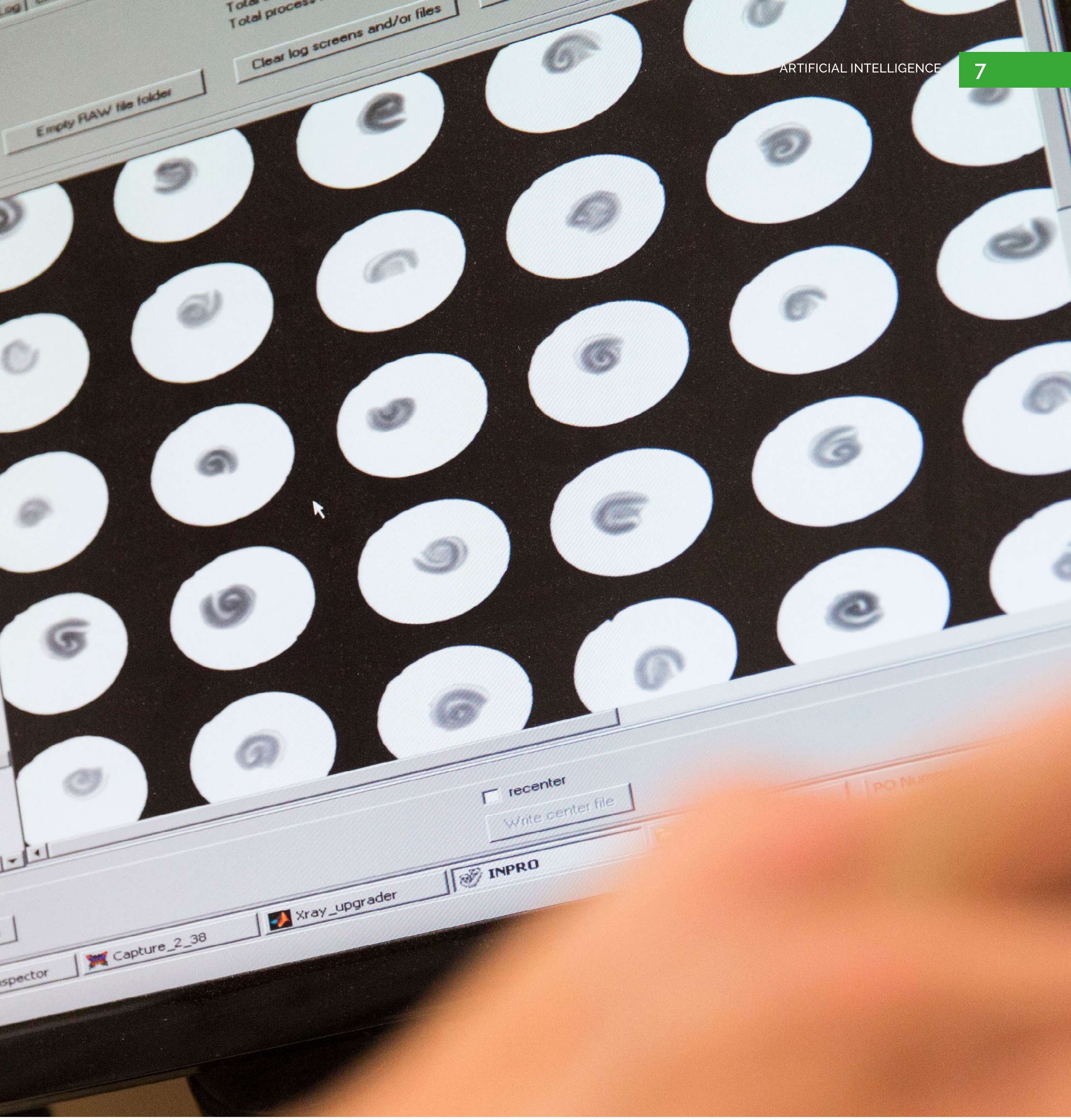
His company has spent years using cameras and sensors to try to bring objectivity to assessing plants and fruit. That data is now a treasure trove for AI predictions. "Recent iterations of AI have suddenly unlocked huge new opportunities from all our historical data," he says. "If it becomes easy to find the needle in a haystack, then it doesn't matter that it's a haystack."

Rijk Zwaan is also exploring how large language models can help combine phenotypic observations with genetic data to predict which varieties will deliver desired traits. "DNA is basically a sequence of letters, and that means it is easier to process with today's large language models than it was with earlier types of AI," adds Otjens. Such genetic insights also stand to drive innovation in the growing market for biological coatings and treatments.

AI also provides a form of quality control, helping improve the value of products by analysing for defects and variability – which are a particular issue in biological products. For example, Incotec, Croda's seed enhancement company, has developed an X-ray imaging tool for tomato seed embryos, where AI compares images with historical germination data, and identifies subtle markers of embryo morphology that predict the likelihood of successful germination. That replaces slow germination tests and destructive sampling with a quick way to remove poor-performing seeds, and create consistent seed lots.

Croda's Dr Marta Dobrowolska-Haywood explains that the real value extends beyond replacing germination tests. "By combining X-ray images with historical germination data, we're turning what was previously just an image into a prediction. That allows customers to identify the best treatments and improve consistency without destroying the seed."

All this matters because the discovery of new crop and seed ingredients is increasingly challenging. Companies need new ways to create products that stand out, and new ways to maximise their lifetime value.



"By combining X-ray images with historical germination data, we're turning what was previously just an image into a prediction."

Dr Marta Dobrowolska-Haywood

A closer connection between researchers and farmers

AI also promises to close the gap between the lab and the field. Enormous amounts of data are gathered in greenhouses and farms on soil conditions, spraying data, humidity, temperature, pathogens and treatment interactions. System level models are emerging that will allow innovators to predict how new products will perform in different environments, which in turn directs innovation to real-world needs. Data on weather will help farmers select the right products for the season ahead.

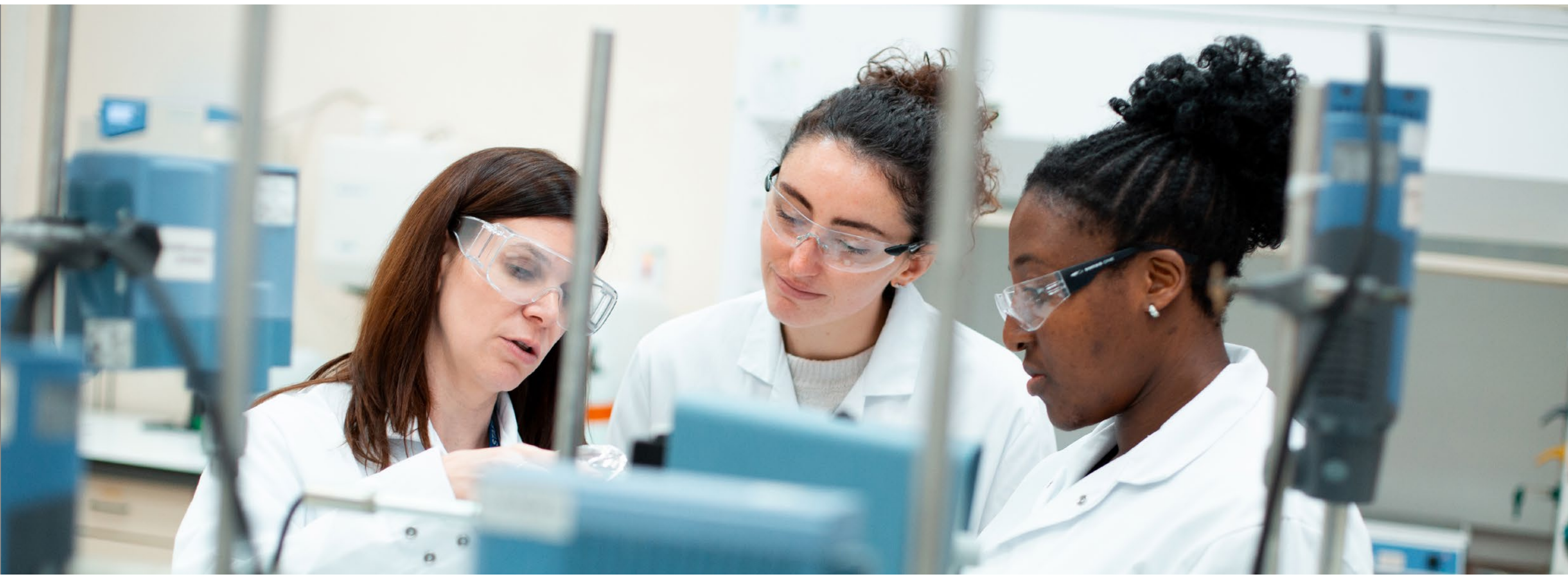
This is not about innovating to order – even if AI slashes time-to-market, regulatory hurdles mean new product development cannot stay ahead of seasonal demands. But models of long-run trends can shape innovation strategies. And with the right portfolio of products, sellers can use AI to provide personalised, data-driven recommendations on the optimal combinations of seeds and treatment, tailored to individual fields and local growing conditions. Agricultural companies may even move from selling products to selling outcomes – providing packages of seed choices, crop treatments, and management recommendations for any set of desired conditions – whether maximising yield, reducing inputs, or improving long-term soil health.

From products to processes

AI is not just about new innovations, but making the process of getting there more efficient, and more enjoyable for researchers.

Several contributors noted AI's potential to automate many documentation and compliance processes, freeing specialists to focus on innovation. Whilst less glamorous, our contributors report that such initiatives prove popular, as they reduce the laborious admin associated with developing seed and crop products.

Even relatively simple AI applications can deliver significant value. Rijk Zwaan, for example, has built an AI-powered product naming system. Tonny Otjens says, "We don't mind coming up with new product names, but it's pretty demotivating when – after waiting for several weeks – it's rejected because it sounds similar to an existing Danish product, or a rude word in Spanish. With AI, they can now generate unique names and screen them against trademark, linguistic and regulatory requirements, reducing a long and unpopular process down to minutes."

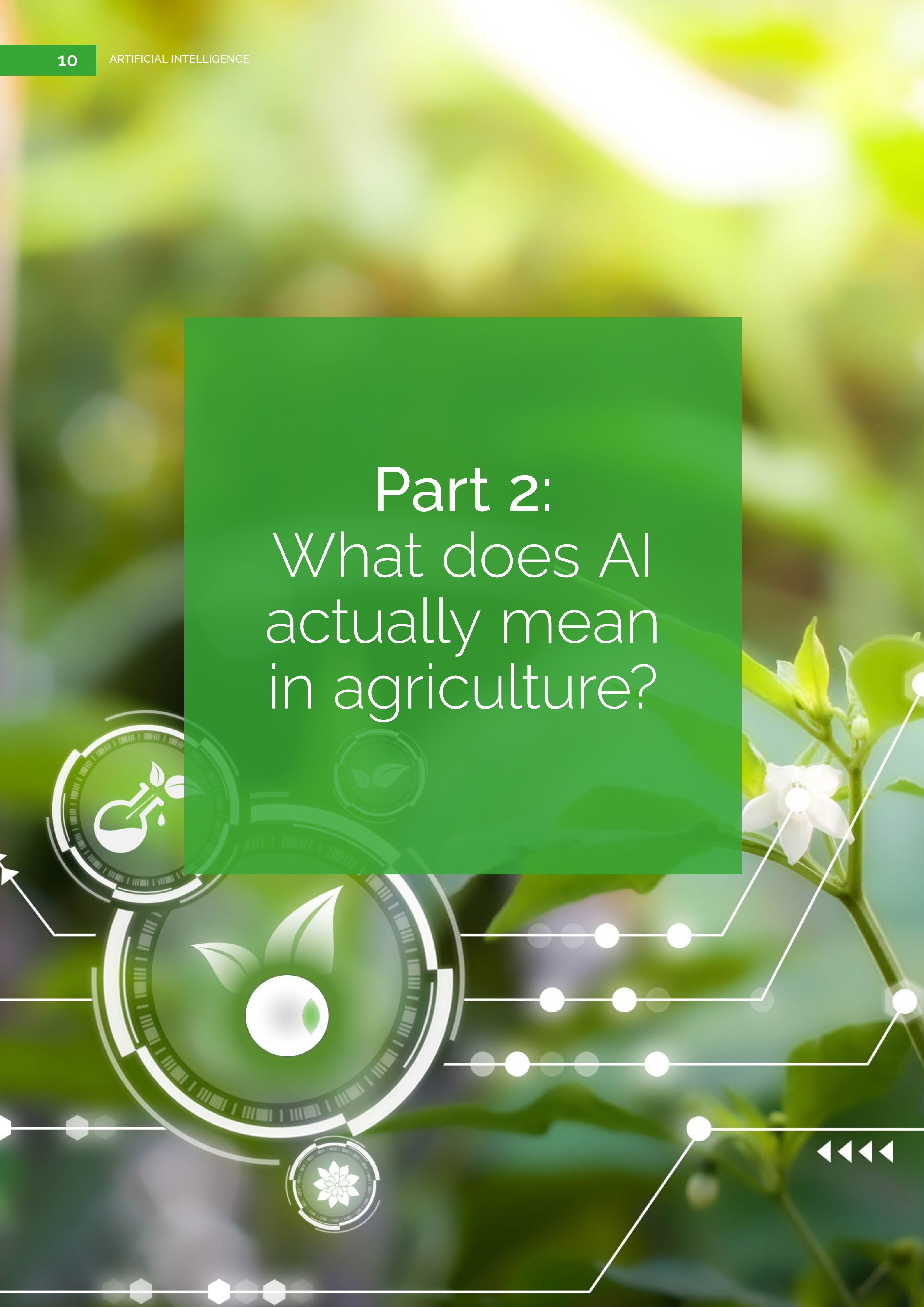


The AI-powered lab?

Some of our experts envisaged the emergence of semi-autonomous research environments capable of designing experiments, generating data, refining models and proposing the next steps, and where many time-draining documentation processes are automated. Scientists would continue to set research priorities, evaluate AI recommendations and make final decisions, but by shifting routine work to AI, organisations could dramatically increase output while reducing innovation costs and time-to-market.

If that vision is realised, agricultural innovators could explore more ideas, test more hypotheses and optimise more products within the same research budget. The resulting explosion in targeted products, combined with more personalised recommendations for growers, would help equip our food system for the growing pressures of climate change, pests, food standards, and global demand for affordable and nutritious food.

Part 2: What does AI actually mean in agriculture?



A single technology?

Artificial intelligence is often discussed as if it were a single technology. In reality, it encompasses a range of tools with different capabilities, each suited to different stages of research and development.

Large language models (LLMs) such as ChatGPT and Claude are general-purpose AI systems trained on vast quantities of public text and data. They are highly effective at interpreting natural language, summarising information and generating ideas. However, on their own they are probabilistic tools – they predict likely answers rather than providing scientifically verified conclusions. This makes them useful for brainstorming and summarising complex information, but less suitable as standalone tools for scientific decision making.

The AI systems likely to have the greatest impact on agricultural innovation are more specialised. These combine LLMs with structured scientific databases, experimental results, laboratory protocols and domain-specific models. Often, they sit on top of "knowledge graphs" – interconnected maps of the company's historical data that link together seeds, traits, formulations, experiments, environmental conditions and outcomes. Rather than simply generating an answer, the AI can query this scientific knowledge base, identify relationships between data points and explain the reasoning behind its recommendations.

As Alister Campbell of Dotmatics notes, scientists increasingly want to "ask a natural language question and get a starting point for the project straight away". Instead of searching through multiple systems, an AI can quickly bring together relevant experiments, literature and internal knowledge into a single response. A seed scientist could ask an AI assistant to suggest a coating formulation for drought-prone conditions. The system might identify relevant historical experiments, compare performance across similar environments, highlight gaps in the available evidence and recommend the next experiments needed to improve confidence in the result. In this sense, AI is more like a research assistant than a tool.

Key concepts: How AI supports innovation

AI includes – or relies upon – a range of technologies that can be used individually or combined to support prediction, optimisation, automation, discovery, and decision support.

Machine learning & neural networks

The 'traditional' sort of AI, which learns patterns from historical data to make predictions or identify relationships that would be difficult for humans to detect. This is the most established form of AI in agriculture and is used for applications such as germination prediction, crop yield forecasting, disease detection, breeding selection and formulation optimisation.

Generative AI

Goes beyond recognising patterns in data to creating new content or ideas based on those patterns. For example, a machine learning model might predict whether a new seed treatment formulation is likely to improve germination. A generative AI model can go a step further by proposing an entirely new formulation for scientists to evaluate.

Knowledge graphs

Not AI per se, but critical to allowing companies to apply AI models to their own data. These are structured networks that connect scientific data, experiments, traits, formulations and environmental conditions, allowing AI systems to reason across multiple sources of information – including company's proprietary scientific data – and explain how it reached its recommendations.

Computer vision

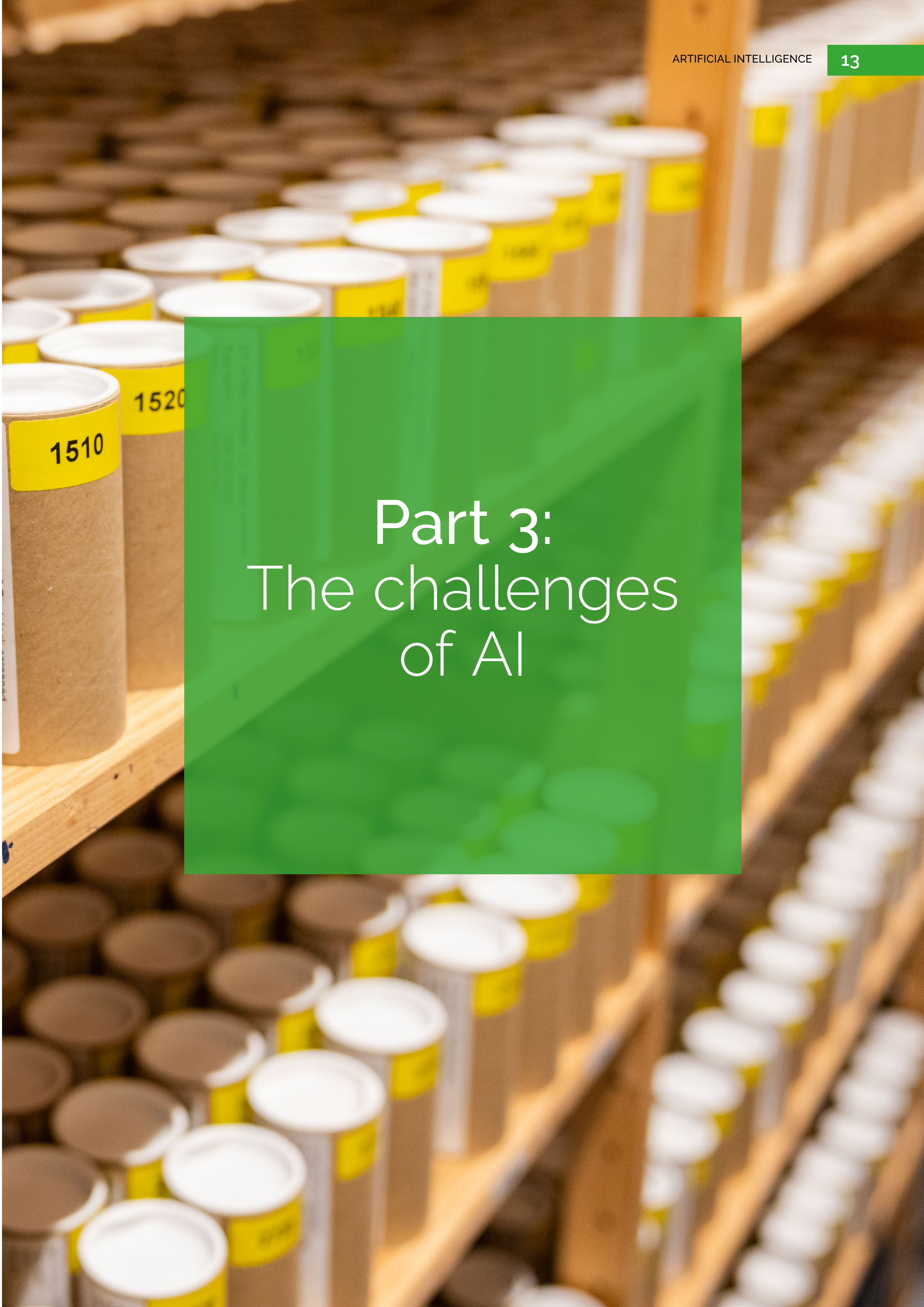
Uses AI to interpret images and video. This is already being used to assess seed quality, analyse plant traits, identify disease symptoms and automate quality assurance.

Large language models (LLMs)

LLMs such as ChatGPT and Claude are well-known examples of generative AI, allowing scientists to search knowledge bases, interrogate research and generate hypotheses using natural language. However, generative AI extends beyond text and image – it can also generate chemical formulations, molecular structures, genetic sequences and other scientific outputs if trained on the right data formats.

Agentic AI

AI agents can plan and execute multi-step tasks with limited human intervention. Multiple specialised AI agents can even work collaboratively on specific sub tasks to achieve a goal. An agentic R&D system might review previous experiments, search scientific literature, identify knowledge gaps, design new experiments and analyse results, passing relevant information to each other to improve answers before recommending the next steps to researchers.



Part 3: The challenges of AI

A broader point of view

Before we consider what AI success looks like, we must acknowledge some challenge areas. Even organisations most advanced in this space acknowledge how much work remains to be done.

Perhaps the biggest challenge is data. AI models depend on large volumes of high-quality information, yet much of the data generated across breeding programmes, formulation development, greenhouse trials and field testing remains fragmented, inconsistent or inaccessible. As Alister Campbell of Dotmatics puts it, "While companies have talked about becoming more data-driven for years, many are still grappling with the practical realities of capturing, standardising and connecting information across functions and systems." However, despite slow progress, some think the growth of LLMs will be a catalyst for change, since their natural language responses make it easy to see what is possible, but also what is missing when they are not properly connected to the company knowledge base.

"If you recommend a treatment for a farm, and it fails, you don't get a second chance."

Stephan Köhler

Trust presents another hurdle. In scientific environments, recommendations need to be understood, not simply accepted. A black box AI answer – however convincing – will not cut it in high stakes situations. "If you recommend a treatment for a farm, and it fails, you don't get a second chance," says Dr Stephan Köhler of BASF.

Then there is the human challenge. AI is becoming increasingly capable, but its success still depends on how effectively organisations combine technology with expertise. "Many skilled employees are still resistant to AI. On the other hand, the next generation of employees is already arriving 'almost AI native.'" says Steve Tharp of Dotmatics. Balancing different needs and attitudes to encourage experimentation whilst managing risk will be a fine line to tread.

Then there's the human challenge. "AI keeps getting more capable, but science never stands still," says Steve Tharp of Dotmatics. "There's always a need to innovate, explore, and push boundaries, and that means constantly pairing the technology with real

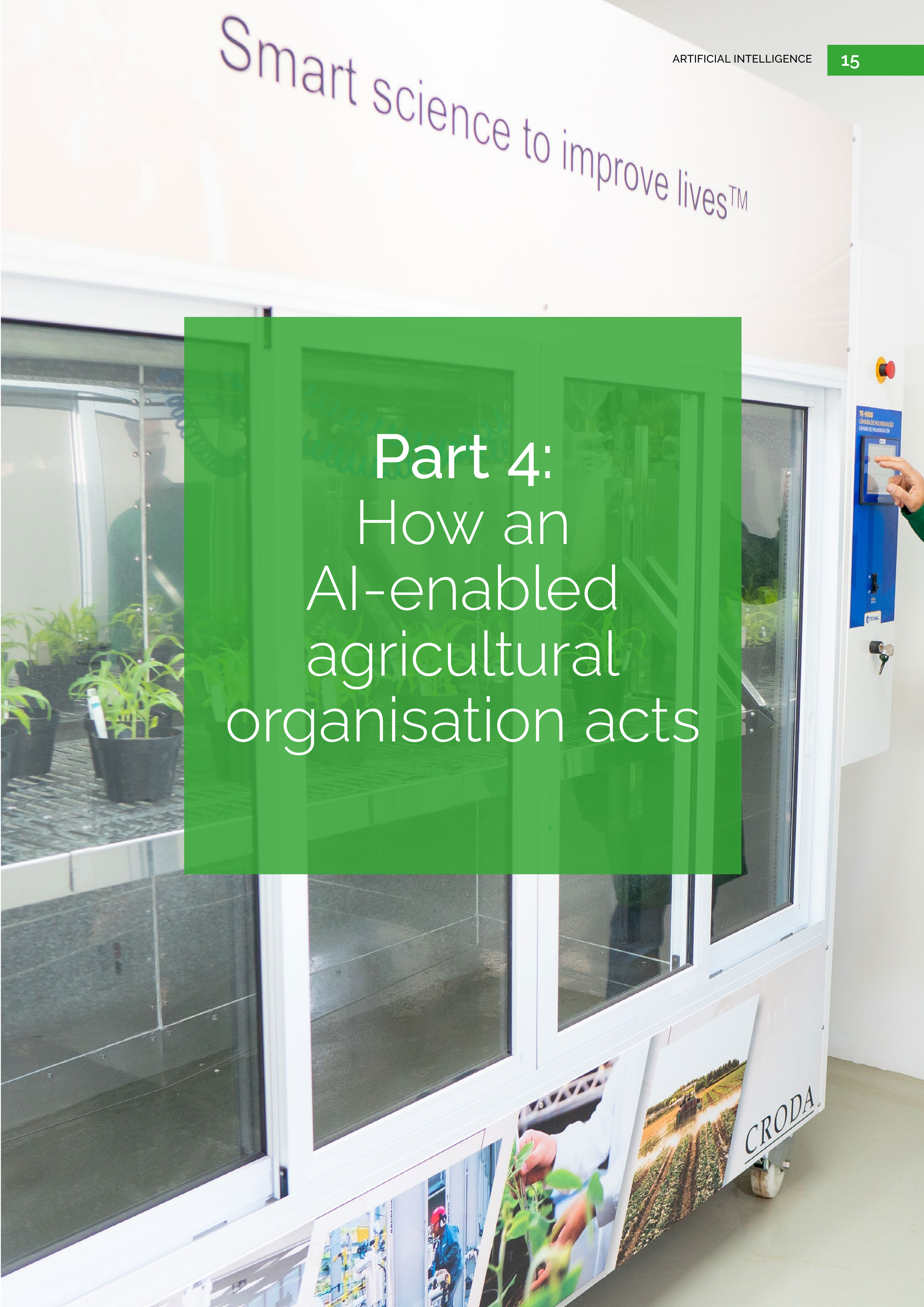
"The next generation of employees is already arriving 'almost AI native"

Steve Tharp

scientific expertise. Skilled researchers trust AI for some tasks but hold back on others. Where a veteran scientist might run an AI-suggested pathway past their own intuition before trusting it, a newer researcher is more likely to take the output and move straight to the next step. The trick is balancing those attitudes: giving people room to experiment while keeping the risks in check"

Another problem that has been little discussed is how the big LLMs will distribute their models in future. No one knows what the business model will be. Prices for tokens are increasing, and none are yet making a profit, raising questions about future costs of AI. Sam Altman has suggested AI may one day be sold like electricity, which may mean organisations need to run AI-efficiency programmes to manage costs. And there is a risk that AI may be distributed unevenly, we have already seen attempts by governments to restrict global access to top models. "Most frontier AI models are built on top of a few big LLMs", says Marc Salomon, "and there are not many alternatives".

These challenges reinforce a broader point. Competitive advantage will come less from deploying AI than from creating organisations capable of supplying it with trusted data, integrating it into scientific workflows and applying expert judgement to its outputs.



Part 4:
How an AI-enabled agricultural organisation acts

Five insights on how to integrate AI

As we have seen, AI is already delivering value across multiple use cases from new formulation to more efficient working practices. But most companies are more ambitious. They want AI to be a disruptive force, making organisations faster, more innovative, and more efficient – but they also need to grapple with how that will change ways of working and business models along the way.

So how could organisations evolve from deploying ad hoc AI projects to having AI ingrained within innovation and business processes, where new AI solutions are trialled, validated and scaled as a matter of routine to create ever more value?

As AI use cases grow, views are converging on how organisations should set themselves up to benefit from AI. In this section, we draw on our contributors' insights to imagine how an AI-enabled agricultural company acts.

1. Treats data as a strategic asset

The AI-enabled agricultural company sees data as a vital business enabler, as important as intellectual property or formulation expertise.

Data is captured systematically across innovation: from laboratory experiments and greenhouse trials to field performance, quality testing and customer outcomes. Information is standardised, tagged with meaningful metadata and made accessible across teams. Databases are connected, searchable and available to both people and machines.

"People often say, 'We have data, let's build an AI model.' But if you only have a handful of data points, you can't really rely on the model's answer," says Marta Dobrowolska-Haywood. "Before you build your model, you need to know how you're collecting data, where it's stored, who can access it and what you'll want to do with it in future. Without that foundation, the ecosystem simply isn't ready."

This includes implementing processes that codify knowledge and understanding into data. "The hard part is capturing why a scientist made a call in the first place, when the reasoning usually only lives in their head," says Steve Tharp of Dotmatics. "That's the missing piece that compounds in value over time with AI, and it's currently the piece most labs still lose". Alister Campbell adds that, "Good models also need data on unsuccessful research, since understanding what failed is as valuable as understanding what succeeded." Failures are ingrained in some researchers' brains, helping them make judgement calls, but companies have a poor record of carefully capturing such data into their systems.

"Good models also need data on unsuccessful research, since understanding what failed is as valuable as understanding what succeeded."

Alister Campbell

Tonny Otjens of Rijk Zwaan says that, "Building high-quality, standardised datasets with well-defined metadata is doing your homework before you can start to do the cool stuff".

Once data is curated, companies can develop foundation models trained on their own scientific and operational data.

Stephan Köhler of BASF describes these as large, pre-trained models that learn underlying physical, chemical, or biological principles before being adapted to specific applications. Such models become a form of institutional memory, capturing decades of expertise and allowing knowledge to be reused across multiple products and research programmes.

Köhler adds that, "The big AI commercial models are commodities, it's not that hard to take a tool like Claude and build a whizzy app. Competitive advantage comes from combining those models with the best proprietary data, scientific expertise and market insight". Companies with significant proprietary data – created or acquired – to channel into models, will have the best models.

2. Redesigns whole processes, not just tasks

Delivering AI value at scale will need a rethink of processes. Tonny Otjens argues that, "Many companies remain focused on local optimisation when they should be looking at the bigger picture". Rather than asking where AI can be inserted into today's workflows, leading organisations should ask how those workflows would be designed if AI had existed from the beginning.

BASF's Stephan Köhler provides an example. Formulation scientists often use their experience to identify promising starting points, then refine them through experimentation towards an eventual product. In an AI world, we might start by generating large volumes of experimental data, training AI systems on those results, and then using the model to explore potential solutions. That shifts some of the duller work to the start, but expands possibilities and accelerates optimisation later. This approach may need new frameworks and systems to capture data, but also a fundamentally different way of thinking about the work.

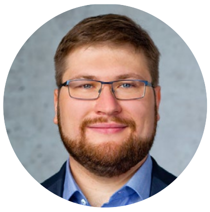
Redesigning whole processes for AI should mean less effort searching for information, compiling reports and analysing data, and more time spent applying judgement, challenging assumptions and making decisions.

3. Builds trust and governance

AI is not just about the most powerful models, but also the most trustworthy. And trust is likely to rise up the agenda as AI moves from 'exciting new experimental technology' to 'business-as-usual'.

Stephan Köhler of BASF argues that, "Explainability is essential because users quickly lose confidence when AI produces recommendations they cannot understand". Marc Salomon goes as far as to suggest that, "In some situations a slightly less capable model may be preferable if its reasoning can be explained clearly".

"Users quickly lose confidence when AI produces recommendations they cannot understand."

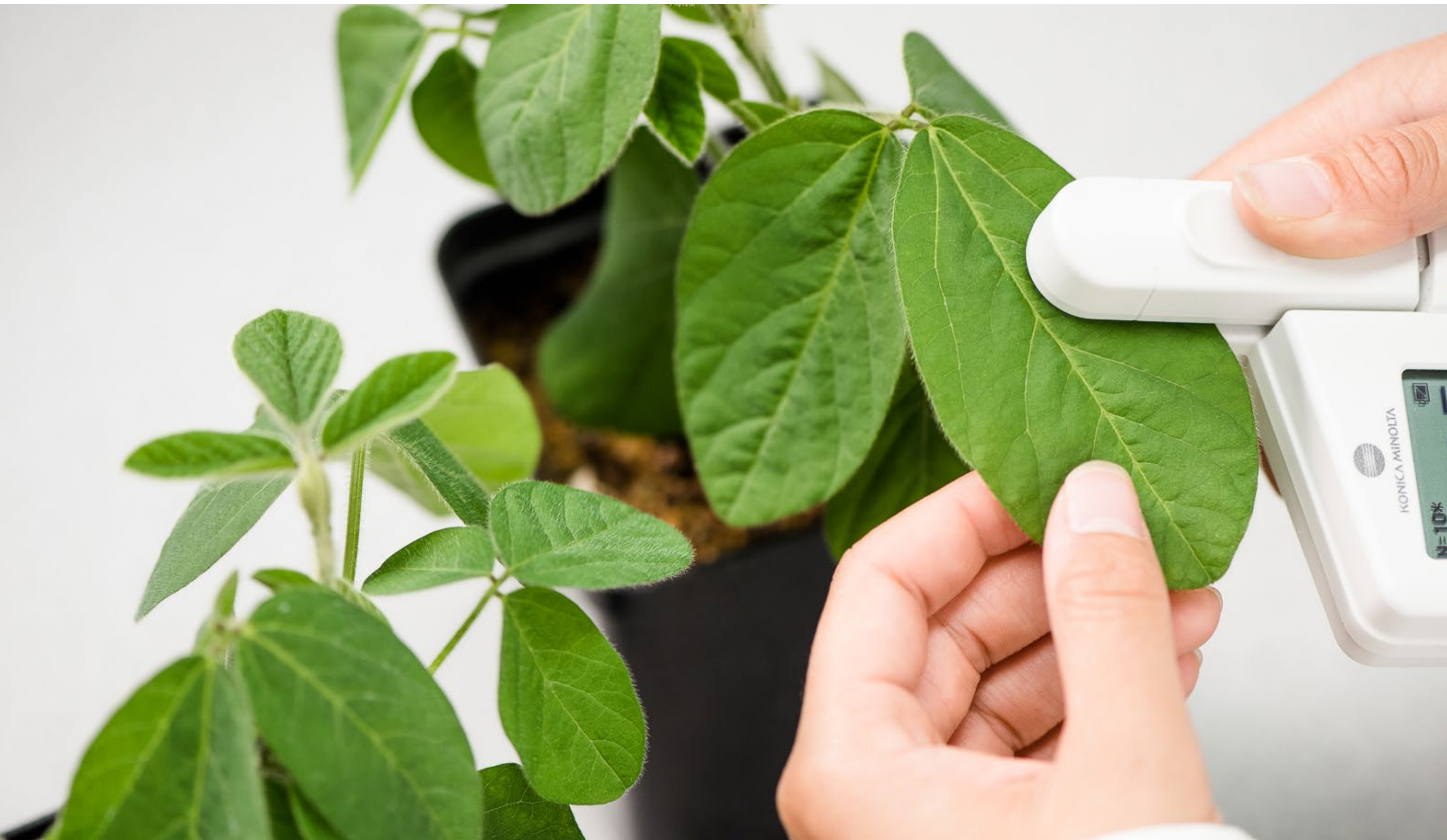


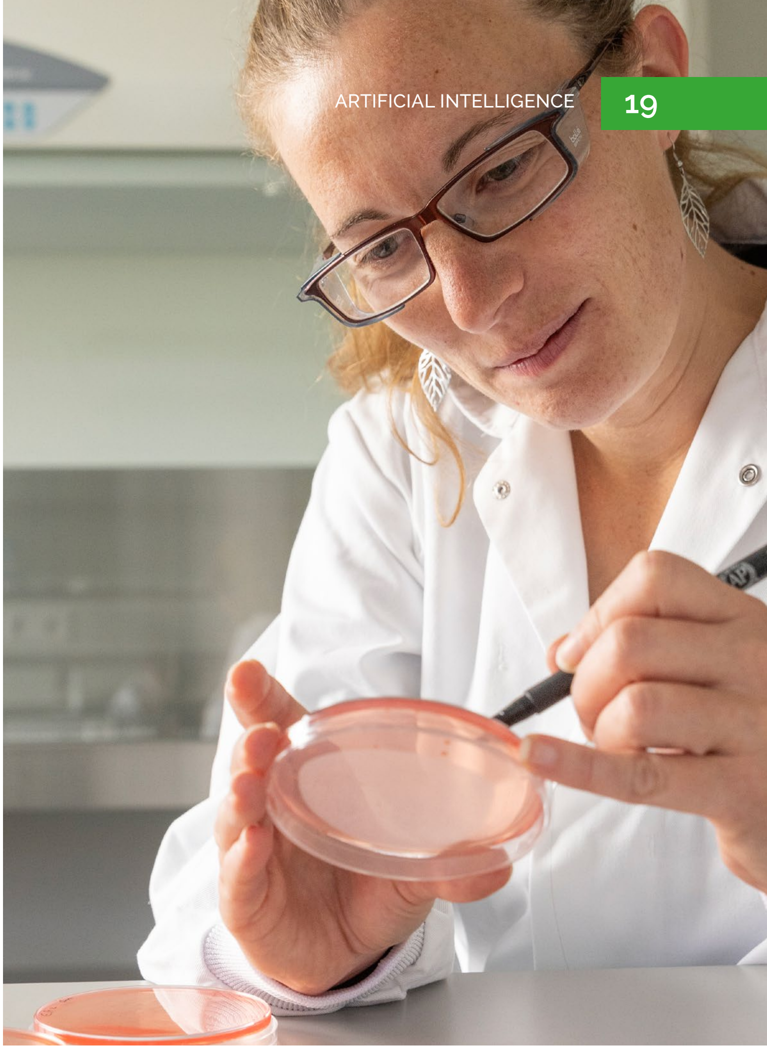
Stephan Köhler

Dotmatics' Campbell says, "The goal here is to create AI that is understandable and shows its working". One of the key tools for doing this, he notes, is 'tool calling', where AI orchestrates queries to specialist scientific software, producing less probabilistic and more deterministic outputs and significantly reducing the risk of hallucinations."

Knowing where the model is uncertain is equally important. Campbell argues that responses should come with confidence levels and caveats, and scientists should be able – and sometimes prompted – to ask questions like "tell me what you don't know; tell me where the data is sparse." Good knowledge graphs, foundation models and approaches such as tool calling will be key to this.

Salomon argues that AI audits will soon become an essential part of responsible innovation. "Many organisations have multiple AI systems in use, but cannot say with confidence where they are, what they are doing or who is accountable for them". For a sector such as agriculture, where AI influences R&D decisions, product recommendations and customer outcomes, that is a serious risk. "A mature organisation needs a record of each AI system, its purpose, its owner, the data it uses, the risks it creates and the controls around it," he says. Companies may not yet feel pressure to invest in this, but it is likely to pay back for those that become leaders in responsible AI, and build the industry trust that comes with it.





4. Creates an AI-ready workforce

The future AI organisation will have teams of people and AI working together. Our experts covered two overlapping strands to this workforce, creating AI and using it effectively.

On one hand, they envisioned a world where researchers manage teams of AI agents. This is not about replacing expertise, organisations need to ensure experts are managing the models to deliver better innovation, not just outsourcing thinking to cut costs. As Stephan Köhler notes, "Market leadership comes not just from great models, but having the best subject matter experts who can ask them the best questions, challenge them, and get the best answers".

Otjens believes this will create more self-sufficient teams. Scientists, breeders and commercial teams will be able to perform tasks that previously required support from specialists, creating a workforce that can spend more time solving problems rather than navigating processes and chains of command.

"Many AI projects fail because they are designed by technical teams without sufficient involvement from users."

Marc Salomon

On the other hand, our experts advocate for a workforce able to not just use AI as a tool, but to think creatively about where it can constantly add new value.

This needs to be nurtured from the bottom up, AI is moving too fast for rigid policies. As Stephan Köhler argues, "Many of the most valuable AI tools emerge from those closest to the work". Successful organisations will give employees access to the latest models and tools, encourage experimentation, and provide routes for them to scale AI tools they have developed.

Tonny Otjens of Rijk Zwaan suggests a good starting point for generating AI enthusiasm is to encourage people to identify the most frustrating or time consuming parts of their job, and explore how to develop AI apps to automate that frustration away. "Solving those everyday challenges builds confidence, and helps employees see AI as a tool that enables them to do their best work", he says. That foundation creates momentum for broader transformation.

Whilst allowing safe experimentation supports AI excitement, well-designed governance is also important, since employees are more willing to use AI when they understand the rules and trust the systems behind them. Otjens adds that, "Companies should give individuals freedom to develop solutions for their own personal and experimental use, whilst also providing guidance and common standards for security, compliance and data management for those who wish to make their AI tools widely available".

Successful organisations will also need a new type of expert employee: translators. These are people who understand both the subject matter and how AI works, says Marc Salomon, who argues that "Many AI projects fail because they are designed by technical teams without sufficient involvement from users, with both teams struggling to speak each other's language. The most successful organisations bridge that gap between the AI model and the real-world application."

5. Operates as part of an ecosystem

Organisations deploying AI at scale will find new demands, from secure storage and compute, to an insatiable appetite for new data to ensure their models remain sector-leading. That will mean new and different relationships with partners and suppliers.

On one side of the ecosystem sit a small number of technology providers supplying models and cloud infrastructure, on which organisations will be highly dependent. Choosing suppliers and managing those relationships – including planning approaches for switching between providers – will become strategically important as the major AI platforms' capabilities, business models and pricing structures evolve.

"A much bigger opportunity comes when AI begins connecting suppliers, manufacturers, customers and growers into a shared innovation ecosystem."

Finn Bauer

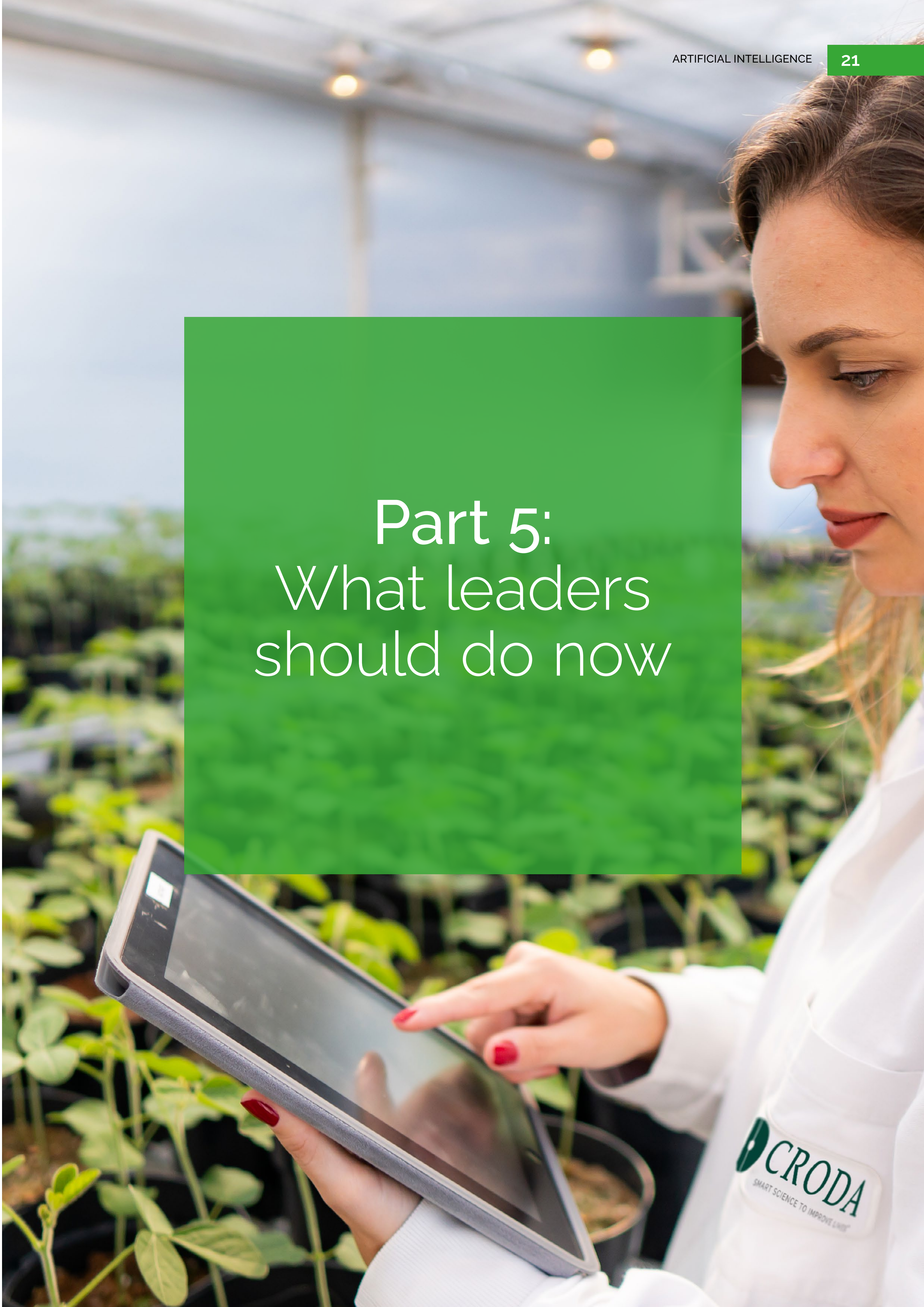
On the other side are the organisations that can add data and value to AI models, including suppliers, universities, startups, and customers. Organisations that can model formulations based on chemical data, supply chain availability, live customer field data, and weather models, will be much better placed to quickly find the best solutions.

Future ecosystems will require secure platforms for sharing data across these different organisations. Some startups are positioning themselves as data sharing hubs, whilst some large organisations are building their own. Köhler describes this as an "underexplored opportunity," adding that, "a platform that allows trusted exchange of data between partners across the value chain would be hugely valuable".

Beyond this, our experts cautiously noted the potential value of sharing precompetitive data to create better models in areas like discovery and formulation that benefit everyone. Initiatives such as the Pistoia Alliance, which supports life sciences companies to share data without compromising commercial advantage, could offer a model for this. A number of privacy-preserving technologies have shown promise for collaboratively training algorithms without exposing underlying sensitive data. This was not seen as easy, but the idea of sharing data to improve models across the board should be an ongoing conversation.

"Most value today is created within individual organisations", says Finn Bauer. "A much bigger opportunity comes when AI begins connecting suppliers, manufacturers, customers and growers into a shared innovation ecosystem."

As AI becomes embedded across agricultural innovation, the companies best able to combine proprietary science with external data, AI capabilities, and trusted partnerships may be the best placed to deliver the best outcomes for growers.



Part 5:
What leaders should do now

Your AI journey

Taking the insight above, we conclude this report with short suggestions for steps organisations can take on their AI journey, based on our contributors' expertise. These are not intended to be prescriptive – we recognise everyone is in a different place when it comes to AI – but a reference for thinking about your own journey.

Build the data foundations

- Treat data accessibility as a strategic priority – AI cannot create value from information that people and systems cannot find or use.
- Build for the data you don't have yet – capture measurements, decisions and the reasoning behind them so future AI systems can learn from both outcomes and expertise.
- Connect systems before building models – AI becomes far more powerful when it can access data, knowledge and tools across the organisation.

Transform processes for the AI era

- Focus on outcomes, not use cases – start with the business problem you want to solve, not the technology you want to deploy.
- Early AI projects can start with tackling day-to-day frustrations – solving everyday pain points is often the fastest route to wider adoption and trust.
- As you mature beyond a bank of early use cases, start to redesign entire processes – the biggest gains come from rethinking entire workflows around what AI makes possible.

Build trust from the start

- Balance freedom with guardrails – make it easy for people to innovate while ensuring data, security and compliance standards are maintained.
- Audit your AI – know which models are being used, what decisions they influence, who owns them and what risks they create.
- Make AI a capability, not a project – the organisations that benefit most will be those that can continuously identify, test, scale and govern new applications.

Set the stage for human-AI teams

- Prepare for human-AI teams – tomorrow's workforce will spend less time gathering information and more time orchestrating AI systems and applying judgement.
- Create a culture of experimentation – employees should feel encouraged to test ideas and explore AI's potential in a safe environment.
- Hire and train translators – people who combine deep scientific expertise with an understanding of AI, ensuring new AI models are grounded in real-world needs.

Establish an ecosystem across the value chain

- Build partnerships across the value chain – the most valuable models will increasingly depend on data, expertise and insights that no single organisation possesses.

Conclusion

AI's greatest contribution to agriculture will not be any single application, but its ability – when deployed smartly and at scale – to change how agricultural innovation happens.

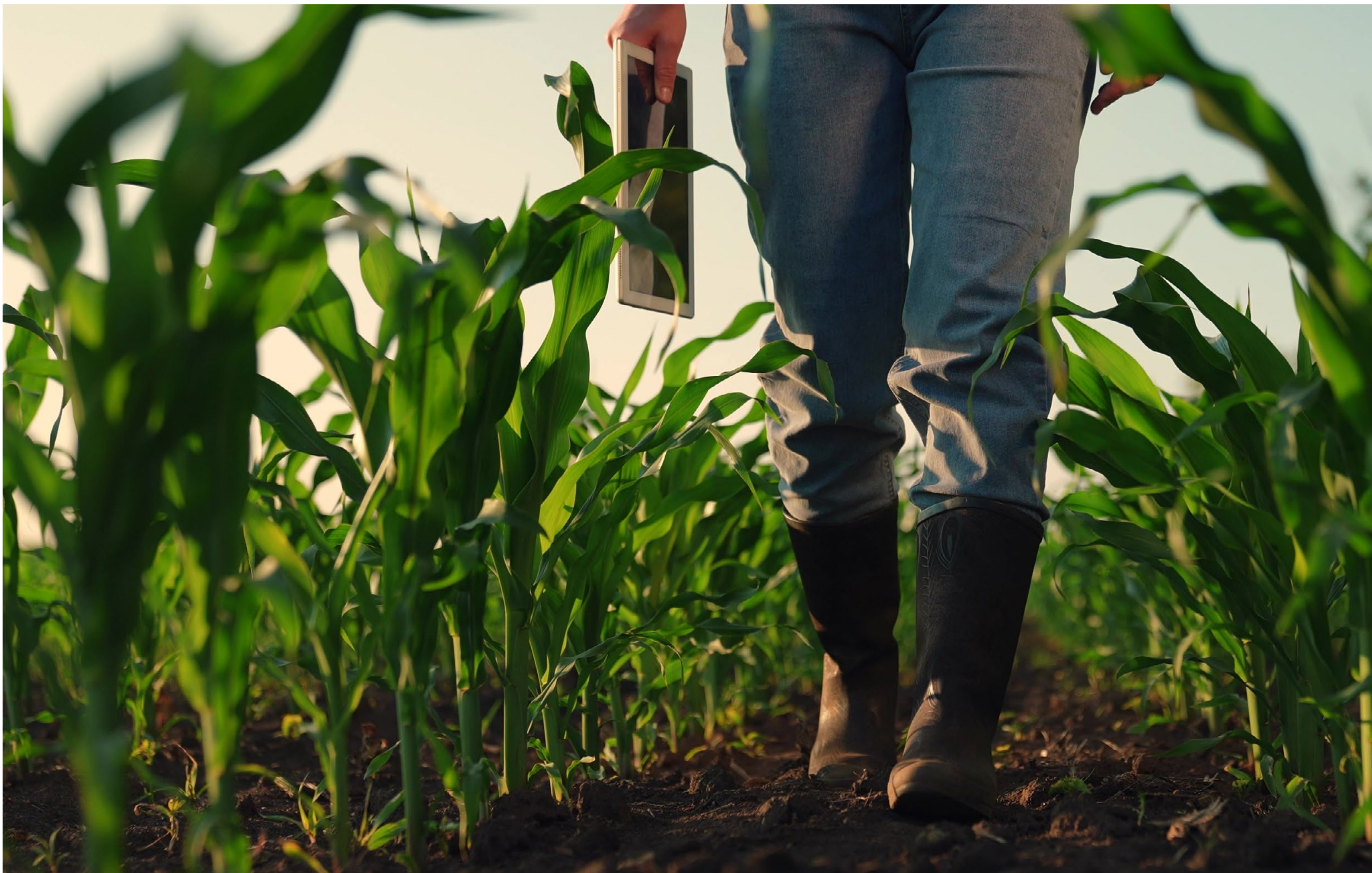
Over the coming decade, organisations that use AI as an opportunity to rethink how they discover, develop and deliver new products will help transform global food systems to meet the challenges before us. By combining AI with proprietary data, scientific expertise and redesigned ways of working, they will be able to explore more ideas, reduce wasted experimentation, bring better products to market faster and provide increasingly personalised recommendations for growers.

The technology is advancing at extraordinary speed. The greater challenge now is organisational readiness. Building trusted data foundations, empowering people to work alongside AI, redesigning processes and creating ecosystems for collaboration will determine who captures the greatest value.

None of that will be easy. It will take ambition, collaboration, and openness to new ways of doing things. Making that happen will require industry-wide conversations to explore ideas and share best practice. This whitepaper hopes to be the start of that conversation by curating expert thinking on AI, but it is by no means the end of it. We at Croda want to be part of that discussion, and we are keen to hear from anyone wishing to explore these ideas further or share their own experiences and challenges with AI.

In a world of climate volatility, growing food demand and increasing pressure on agricultural productivity, AI has arrived at an opportune moment. We must work together to ensure the whole agricultural industry benefits, alongside everyone who depends on it.

To discuss the findings of this report, contact Finn Bauer, Vice President of Research and Development for Life Sciences, Croda: Finn.Bauer@croda.com.



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