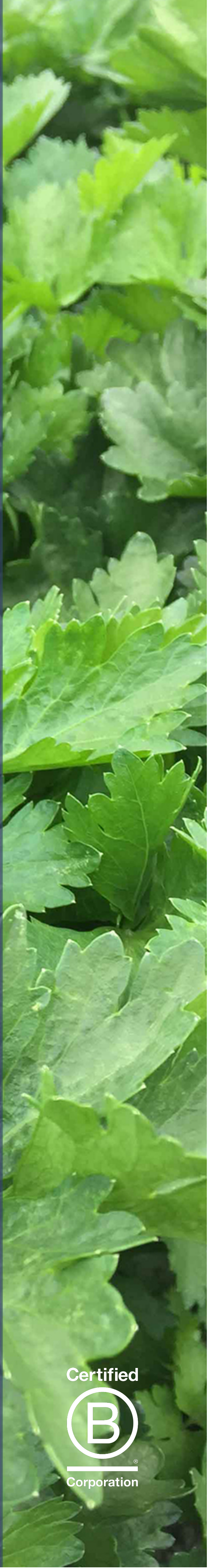
OCTOBER 2025

Exploring AI Applications for the Vegetable Industry (VG24008)

Final Report

Hort Innovation



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Executive Summary

The *Exploring AI Applications for the Vegetable Industry (VG24008)* project was commissioned by Hort Innovation to identify, assess, and prioritise how artificial intelligence (AI) can enhance the efficiency, profitability, and sustainability of the Australian vegetable sector.

Delivered collaboratively by RM Consulting Group (RMCG) and the Australian Regional AI Network (ARAIN), the project combined national industry consultation with a structured feasibility assessment of 27 AI technologies to create a practical, evidence-based roadmap for future investment.

PURPOSE AND APPROACH

The project focused on real-world applications that deliver measurable benefit for growers and:

- Identify 3–5 high-impact AI opportunities for the vegetable industry
- Assess technical, commercial, and adoption feasibility across available technologies
- Develop a staged roadmap for capability building, piloting, and long-term integration.

The methodology combined national engagement, through three regional workshops (Victoria, Western Australia and Queensland), two Strategic Investment Advisory Panel (SIAP) sessions, and a national online webinar.

More than 100 growers, advisors, and supply-chain representatives contributed, ensuring that outcomes reflected practical, on-farm realities.

KEY CONSULTATION FINDINGS

Consultation confirmed that while awareness of AI remains low, interest and confidence grow rapidly once growers experience practical demonstrations.

Across all regions, participants identified consistent needs and opportunities for the adoption of AI:

- Simplifying compliance and documentation through generative AI
- Improving labour efficiency and workforce safety via multilingual training tools
- Enhancing crop forecasting and scheduling with predictive analytics
- Reducing costs and waste through automated quality assurance
- Fostering local innovation through open-source, grower-driven projects, e.g. Open Weed Locator (OWL).

Barriers identified included data trust, subscription fatigue, connectivity, and digital literacy. However, participants consistently emphasised that adoption would depend on clarity of value, demonstrable time savings, and trusted delivery channels.

The project adopted a “confidence-first” approach, focusing on awareness, skill development, and small-scale, evidence-driven adoption before large-scale automation or advanced data integration.

FIVE HIGH-IMPACT AI OPPORTUNITIES

The feasibility assessment identified five AI applications with the greatest potential to deliver measurable, near-term benefits for the Australian vegetable industry. These priorities were selected because they align closely with grower-identified challenges, demonstrate sufficient technical maturity, and offer strong potential to improve efficiency, decision-making, and sustainability.

Together, these five areas, as outlined in Table ES-1, represent a balanced portfolio across production, post-harvest, and business management functions, combining proven, emerging, and future opportunities.

Table ES-1: Identified high impact AI Opportunities

Priority Area	AI Type	Focus / Example	Current Status	Recommended Next Step
AI Disease Detection	Narrow (Computer Vision)	Automated identification of pest/disease symptoms from images	Medium readiness	Pilot / trial under Australian conditions
Generative AI Agronomy Advisors	Generative	Context-specific support for decision-making, compliance and reporting	Medium–high readiness	Pilot / adapt for local context
Autonomous & Precision Weeding	Narrow / Agentic	Service-based robotics for mechanical and targeted weed control	Medium-high readiness	Pilot / field validation and service model design
Vision-Based Quality Assurance	Narrow	Automated grading and defect detection in packing lines	High readiness	Adopt now / demonstrate ROI through case studies
AI for Seed & Variety Selection	Generative / Predictive	Matching genetics to micro-climates and production systems	Early commercial	Pilot / integrate with existing research networks

IMPLEMENTATION ROADMAP

To translate findings into coordinated action, the project developed a three-horizon roadmap, outlined in Table ES-2, representing a staged, scalable approach to building capability and adoption across the industry.

Each horizon reflects a step in maturity rather than a fixed timeframe, recognising that regions and businesses will progress at different speeds depending on readiness and opportunity.

Table ES-2: AI Implementation Roadmap for the Australian Vegetable Industry

Horizon	Focus	Key Actions	Intended Outcomes
1. Capability & Confidence (0–12 months)	Build awareness and foundational skills.	Deliver AI literacy training through VegNET; produce prompt libraries and video explainers; support low-risk use (e.g. generative AI for admin tasks).	Grower confidence and trust; early adoption of accessible tools; shared understanding of AI's practical value.
2. Applied Pilots (1–3 years)	Demonstrate measurable value through grower-led pilots.	Trial the five priority AI applications; use consistent evaluation metrics; share findings through regional networks and national case studies.	Evidence base for ROI and usability; scalable, context-tested models ready for commercialisation.
3. Systems & Trust (3–5 years +)	Establish data standards, governance, and infrastructure.	Develop interoperability frameworks; embed ethics, privacy, and validation pipelines; align with national responsible-AI policies.	Trusted, transparent AI ecosystem enabling safe, large-scale adoption across the vegetable industry.

This roadmap prioritises future investment in capability, ensuring that adoption is practical, equitable, and grounded in real-world value before progressing to complex automation.

As with any emerging technology, this roadmap should be viewed as adaptive rather than fixed. The project recognises that artificial intelligence is a rapidly evolving field, with new tools, models, and governance frameworks emerging almost monthly. The findings and recommendations in this report reflect the best available evidence as of October 2025. Ongoing monitoring, review, and adaptive planning will be essential to ensure future investments remain relevant, effective, and aligned with industry and regulatory developments.

CONCLUSION

This report presents a clear, evidence-based roadmap for advancing AI within Australia's vegetable industry.

It confirms that the opportunity is real, the technology is ready, and the industry is curious, but successful adoption depends on confidence, collaboration, and context.

By investing first in people, validating technology through practice, and embedding trust through transparent systems, Hort Innovation and its partners can ensure that AI becomes not just a technological advancement, but a practical enabler of resilience, efficiency, and competitiveness for vegetable growers nationwide.

ACKNOWLEDGEMENT OF COUNTRY

We acknowledge the Traditional Owners of the Country on which we work throughout Australia and recognise their enduring connection to the land, waters, and culture. We pay our respects to their Elders, both past and present, and acknowledge emerging leaders. Furthermore, we express our gratitude for the knowledge and insights that Traditional Owners and other Aboriginal and Torres Strait Islander peoples contribute to our collective work in Australia.

We extend our respects to all Aboriginal and Torres Strait Islander communities. We acknowledge that Australia was founded on the genocide and dispossession of First Nations peoples and affirm that sovereignty was never ceded in this country. We embrace the spirit of reconciliation, striving towards self-determination, equitable outcomes, and an equal voice for Australia's First Peoples.

1 Introduction

1.1 BACKGROUND AND RATIONALE

Artificial intelligence (AI) is reshaping how agriculture operates, from how data is collected and interpreted to how decisions are made in the paddock, packing shed, and along the supply chain. Across the sector, AI is being used to analyse complex information in real time, automate repetitive tasks, and improve forecasting accuracy. These capabilities are creating new opportunities for productivity gains, labour efficiency, and resource optimisation that were not previously achievable.

While many vegetable producers already use digital tools such as sensors, satellite imagery, or farm management software, the emergence of generative and integrated AI systems represents the next step in agricultural innovation. These technologies can simplify compliance, reduce inputs, enhance decision-making, and open new avenues for collaboration across the value chain.

For most Australian vegetable growers, however, AI remains largely untested. The potential is significant, but so too are the barriers, with uncertainty about relevance, trust in data and algorithms, subscription fatigue, and varying levels of digital literacy. This project was designed to help bridge that gap. Through targeted engagement with growers, industry bodies, and technology specialists, it explored how AI can move from concept to practical application within the Australian vegetable sector.

1.2 PROJECT PURPOSE

The *Exploring AI Applications for the Vegetable Industry (VG24008)* project was commissioned by Hort Innovation to identify, evaluate, and prioritise the most promising applications of AI within Australia's vegetable sector.

The project brought together growers, industry leaders, and technology specialists to ensure AI solutions are not only innovative but also practical, scalable, and commercially valuable.

The project sought to:

- Identify 3–5 high-impact AI opportunities that can improve efficiency, profitability, and sustainability in vegetable production and business management
- Assess the feasibility, commercial readiness, and adoption complexity of emerging AI technologies
- Define a staged roadmap to guide industry investment—from building awareness and confidence to piloting applied technologies and preparing for future, system-level adoption.

The project was delivered collaboratively by RM Consulting Group (RMCG) and the Australian Regional AI Network (ARAIN), combining agricultural extension expertise with applied AI capability.

1.2.1 PROJECT CONTEXT AND ALIGNMENT

This project sits within the broader digital transformation of Australian agriculture and aligns directly with the Vegetable Strategic Investment Plan (SIP) priorities of labour efficiency, sustainability, and technology adoption.

It connects with Hort Innovation's AgTech and Automation portfolio and supports national initiatives such as the National Robotics Strategy and the Australian Government's Digital Agriculture agenda.

Importantly, the project also contributes to early thinking for VegNET Phase 4 (2026–2030), which aims to strengthen regional extension networks and integrate AI-enabled tools into day-to-day industry engagement.

Embedding AI capability within trusted, levy-funded programs such as VegNET and Soil Wealth Integrated Crop Protection (ICP) provides a scalable, low-risk pathway for building confidence and capability across the sector.

1.3 REPORT STRUCTURE

This report outlines the context and methodology through to findings, feasibility analysis, and a staged roadmap for investment and adoption. Specific sections in the report include:

1. **Introduction** – Project overview, context, and alignment
2. **Methodology** – Approach to consultation, analysis, and assessment
3. **Global and Australian AI Landscape** – Summary of global benchmarks and emerging trends
4. **Industry Consultation Findings** – Insights from growers, stakeholders, and workshops
5. **Feasibility and Readiness Assessment** – Evaluation of 27 AI technologies using a structured framework
6. **Implementation Roadmap** – Practical roadmap for industry investment
7. **Conclusion and Recommendations** – Summary of findings and future directions for AI adoption in the vegetable industry.

2 Methodology

2.1 OVERVIEW OF APPROACH

The project adopted a structured, evidence-based approach to explore how AI can deliver tangible benefits across the vegetable supply chain. It integrated both qualitative engagement (through national consultation) and quantitative analysis (through feasibility assessment and market review) to ensure recommendations were grounded in both grower experience and commercial reality.

A framework to considering the opportunities for AI application in vegetable businesses was developed at the commencement of the project, as outlined in Figure 2-1, and supported areas of focus through the industry consultation.

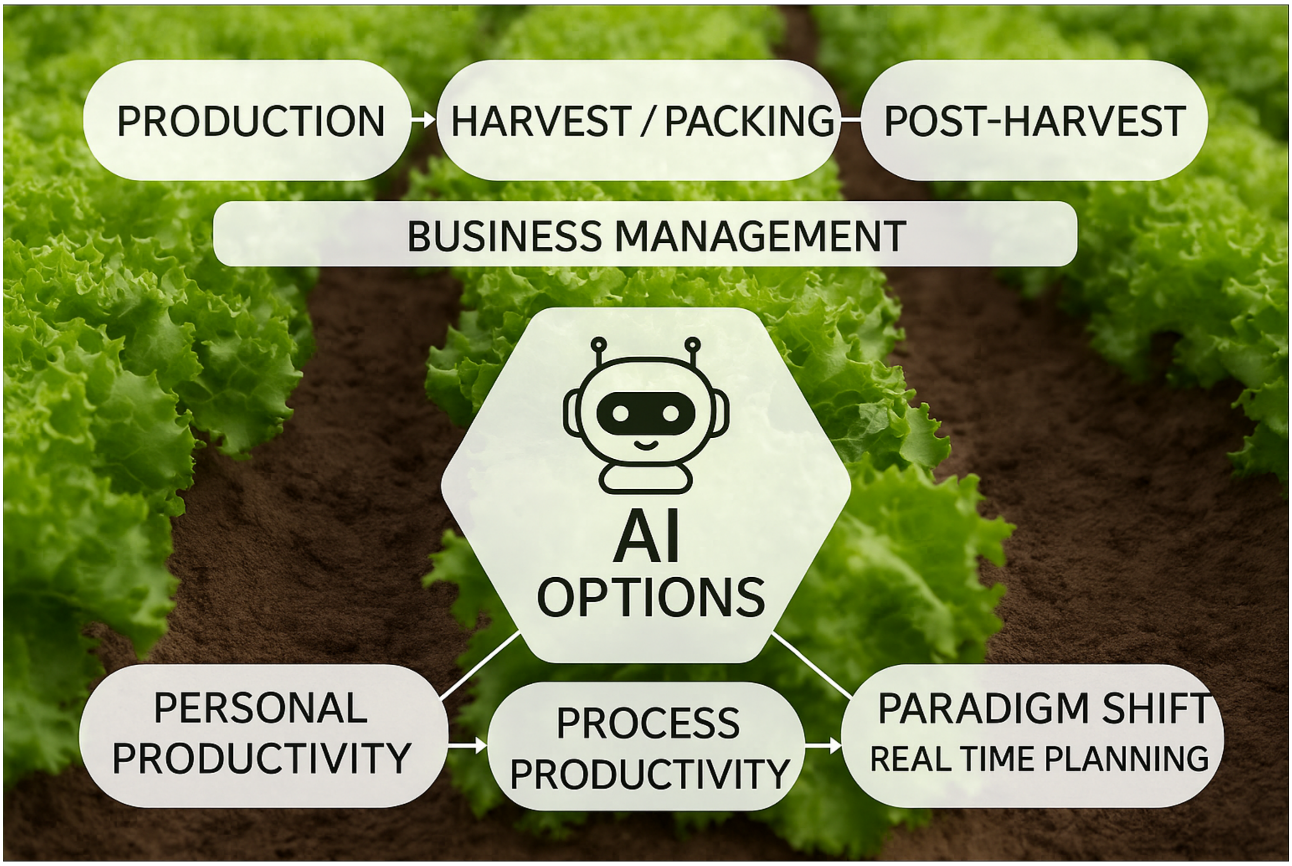

Figure 2-1: Framework for exploring AI opportunities in the vegetable industry

This framework reflects the project's balance between engagement, research, and validation, ensuring AI opportunities were explored through the lens of both user relevance and implementation feasibility.

The project was delivered through three sequential and interconnected phases:

1. **Scoping and framing** – Reviewed existing agtech literature, international case studies, and domestic baseline data to define categories of AI application and develop engagement tools and materials
2. **Consultation and validation** – Conducted regional, national, and online workshops to capture grower perspectives, identify opportunities, and test feasibility across production and business functions
3. **Analysis and synthesis** – Integrated qualitative feedback and quantitative evidence to develop a structured feasibility assessment and prioritised roadmap for AI adoption in the vegetable industry.

2.2 CONSULTATION DESIGN AND DELIVERY

2.2.1 ENGAGEMENT OBJECTIVES

The engagement process through the project was designed to:

- Capture grower and supply-chain perspectives on where AI could add value within production, post-harvest, and business management systems
- Identify practical and high-impact opportunities for short- and medium-term application
- Test the feasibility and relevance of emerging AI technologies for different production contexts and regions
- Build awareness and confidence in AI through practical, non-technical demonstration and discussion.

This participatory approach supported both industry learning and co-design of the recommendations, ensuring grower input shaped the project's direction and outcomes.

2.2.2 CONSULTATION ACTIVITIES

A series of five structured engagement activities were delivered between June and November 2025, including Strategic Investment Advisory Panel (SIAP) presentations, three regional workshops, and a national online webinar as outlined in Table 2-1.

Table 2-1: Project Consultation Activities

Engagement	Date	Format / Host	Focus and Outcomes
SIAP Briefing – Vegetable Strategic Investment Advisory Panel	26 June 2025	In-person hosted by Hort Innovation Vegetable SIAP	Introduced project objectives, initial scoping framework, and early examples of AI in agriculture; gathered feedback to shape consultation design.
Victorian Workshop – AUSVEG Boardroom, Glen Iris	14 August 2025	In-person, hosted by AUSVEG and AUSVEG Vic (VegNET)	Introduced AI fundamentals; identified business management challenges where AI could assist (compliance, workforce management, QA systems).
Western Australian Workshop – Manjimup (Tall Timbers Brewery)	9 September 2025	In-person, hosted by Warren Cauliflower Improvement Group and VegetablesWA (VegNET)	Tested perceptions of AI in production; identified connectivity and interoperability barriers; highlighted potential for grower-led tools such as OWL.
Queensland Workshop – Bundaberg AgroTrend AgTech Showcase	26 September 2025	In-person, hosted by Bundaberg Fruit and Vegetable Growers (VegNET) and Regional Business HQ Wide Bay	Explored applied production uses (forecasting, pest detection); linked AI opportunities to existing mechanisation and robotics programs.
SIAP Briefing – Vegetable Strategic Investment Advisory Panel	17 October 2025	In-person and online hosted by Hort Innovation Vegetable SIAP	Presented draft findings and feasibility results for validation and refinement of recommendations.
National Online Webinar – *AI unpacked: Practical tools for vegetable growers*	6 November 2025	Online, co-hosted with Soil Wealth ICP	Shared grower-led case studies and live demonstrations of generative AI tools; extended reach to national participants and reinforced industry appetite for practical, hands-on learning.

The industry consultation workshops followed a similar four-step facilitation framework:

1. **Demystify** – A short, non-technical introduction to AI and how it is already used in agriculture
2. **Demonstrate** – Live or recorded demonstrations of AI tools in action (e.g. generative AI for documentation or translation)
3. **Discuss** – Interactive mapping of pain points and opportunities across production, harvest, and business functions
4. **Define** – Prioritisation of top AI use cases based on relevance, impact, and feasibility.

This consistent design ensured comparability between regions and generated a rich dataset of grower perspectives to inform the feasibility assessment.

2.2.3 PARTICIPANT PROFILE

Engagements included a cross-section of the vegetable industry value chain, ensuring the findings reflected diverse operational, technical, and strategic perspectives. Participants included:

- Commercial vegetable growers from small to large enterprises across multiple production systems
- Supply chain and service partners, including packers, processors, and logistics providers
- Industry development and extension staff (e.g. VegNET Industry Development Officers)
- Researchers, consultants, and representatives from AUSVEG, Hort Innovation, and other industry associations.

This diversity of participation helped identify both shared challenges and region-specific priorities, creating a nuanced understanding of AI readiness across the sector.

2.3 ANALYTICAL FRAMEWORK

2.3.1 MULTI-CRITERIA FEASIBILITY ASSESSMENT

Building on workshop outcomes, the project team undertook a structured AI Feasibility Assessment to evaluate 27 AI-enabled technologies relevant to vegetable production, post-harvest operations, and business management. Each technology was evaluated across four dimensions:

- **AI Type** – Narrow (task-specific), Generative (content creation), or Agentic (autonomous systems)
- **Commercial Readiness** – Availability and demonstrated performance
- **Adoption Complexity** – Integration effort and change management required
- **Implementation Cost** – Indicative capital and subscription investment.

The approach and results are detailed further in Section 5. Technologies were categorised into three decision pathways:

- **Adopt Now** – Proven ROI and low integration complexity
- **Pilot / Trial** – High potential requiring field validation
- **Monitor** – Longer-term, emerging opportunities (3–5+ years).

2.3.2 DEVELOPMENT OF IMPLEMENTATION ROADMAP

Insights from the national consultation were combined with the results of the AI Feasibility Assessment to develop a practical, staged implementation roadmap for the vegetable industry.

This synthesis involved mapping grower-identified priorities and perceived barriers against the assessed readiness, cost, and complexity of each technology. Through this process, applications were grouped into short, medium, and long-term adoption horizons based on their feasibility, scalability, and alignment with current industry capability.

This staged model, referred to throughout the report as the "confidence-first" approach, provided the foundation for the three-horizon roadmap outlined in Section 6. It ensures that recommendations are grounded by evidence, trust, and capacity building before scaling to more complex, system-wide technologies.

2.4 LIMITATIONS

As with any exploratory project operating in a rapidly evolving technological domain, several limitations should be acknowledged when interpreting the findings of this report. These limitations reflect both the scope of the project and the nature of the engagement methods used.

- **Focus on generative AI** – Workshop activities intentionally centred on generative AI to build familiarity and confidence among participants through accessible, hands-on demonstrations. While this provided valuable insights into user readiness and perceived value, it did not include detailed field testing of other AI types, such as agentic or predictive automation systems. The feasibility assessment therefore complements these discussions by examining a broader spectrum of technologies beyond the workshop focus.
- **Qualitative sampling** – Engagement outcomes were drawn from a targeted but limited group of participants, including growers, advisors, and supply-chain representatives who were willing and available to participate. While diverse in geography, production system, and enterprise scale, this cohort represents an engaged cross-section rather than a statistically representative sample of the wider vegetable industry.
- **Evolving technology landscape** – The pace of AI development is exceptionally rapid, with new models, plug-ins, and applications emerging monthly. The findings presented in this report reflect the best available evidence as of October 2025, but continued monitoring will be essential to maintain currency and relevance as the technology and regulatory environment evolve.
- **Variable data availability** – Some technologies assessed through the feasibility framework have limited public performance data or are subject to proprietary commercial constraints. Where possible, this was mitigated through cross-referencing international benchmarks and verified case studies.

Despite these constraints, the mixed-method approach, combining consultation, literature review, and structured feasibility analysis, provided a robust, triangulated evidence base. Collectively, these methods ensure that the roadmap and recommendations presented in this report are both credible and practical, reflecting the realities of current technology readiness and industry capability.

3 Global and Australian AI Landscape

3.1 OVERVIEW

AI is evolving rapidly from concept to commercial reality across all sectors, including agriculture. Early agricultural applications have been in place for more than a decade, focused on narrow, task-specific systems such as image recognition and predictive analytics. Today, advances in computing power, data availability, and cloud infrastructure have enabled a new generation of AI tools that are more adaptive, intuitive, and accessible to farmers and advisors.

Globally, AI is being used to monitor crops, forecast yields, optimise irrigation, detect pests and diseases, automate grading, and improve supply-chain traceability. Investment in AI-enabled agtech has grown sharply over the past five years, with leading markets such as North America, Europe, and East Asia moving from research pilots to commercial deployment at scale.

For the Australian vegetable industry, this evolution presents a significant opportunity. Many businesses already collect digital data through sensors, drones, or farm-management platforms, but few have applied AI to interpret that data or automate decisions. Understanding how AI has developed, and which types are most relevant to vegetable production, is the first step toward confident and informed adoption.

3.2 EVOLUTION OF AGRICULTURAL AI

AI in agriculture has developed over more than a decade, evolving through distinct but overlapping phases that reflect both technological maturity and user accessibility.

Understanding this progression is essential for identifying where the vegetable industry is currently positioned, and to identify future opportunities.

3.2.1 NARROW AI – TASK-SPECIFIC SYSTEMS

The first phase of agricultural AI has been dominated by narrow, single-purpose applications. These systems use machine learning and computer vision to perform well-defined tasks such as detecting pests and diseases, guiding autonomous weeding, or analysing satellite imagery for yield prediction.

Narrow AI has already been widely adopted in parts of Australian agriculture, particularly through contractors and service providers offering drone mapping, soil analysis, or machine-vision weeding. However, the benefits of these systems are often limited to one function or data source, with insights typically remaining within external platforms rather than being integrated into farm-level decision-making.

This “single-use” nature means that while narrow AI is proven and valuable, it has not fundamentally changed how most vegetable businesses operate day-to-day or address holistically the key systematic changes that exist within business structures.

3.2.2 GENERATIVE AI – CONTENT CREATION AND INTEGRATED DECISION SUPPORT

The emergence of generative AI has represented a major shift in accessibility and flexibility of the technology.

Powered by large language models (LLMs) and multimodal systems, generative AI can create new content, text, images, or summaries, from existing data. In agriculture, this means growers can now use AI directly to generate compliance reports, training materials, or data summaries without relying on third-party systems.

This transition is a catalyst for change. Instead of AI being something done *for* growers by external providers, it can now be used *by* growers as a daily business tool. Generative AI allows for more bespoke, integrated use, helping growers translate field data into insights, automate record-keeping, and communicate with diverse workforces.

The release of publicly accessible tools, such as ChatGPT (late 2022) and open-source LLM frameworks, has democratised AI, enabling widespread experimentation and adaptation at low cost. These technologies also form the bridge between narrow and fully autonomous systems, as they can interpret unstructured data, synthesise recommendations, and interact with multiple digital tools through plug-ins and application programming interfaces (APIs).

3.2.3 AGENTIC AI – AUTONOMOUS AND ADAPTIVE SYSTEMS

The next phase is agentic AI, this includes systems capable of autonomous decision-making across multiple domains.

These models combine perception (sensing), cognition (reasoning), and action (execution), allowing AI "agents" to operate with minimal human input. In agriculture, this could include fleets of collaborative robots, integrated crop-forecasting networks, or digital-twin farms that plan and optimise operations continuously.

Agentic AI is still in the research and early-prototype phase but is advancing rapidly through developments in loop (continuous feedback) and mesh (networked agent collaboration) architectures. These frameworks allow multiple AI agents to interact dynamically, sharing data, verifying outcomes, and improving performance over time.

In practice, this could enable a network of AI systems that coordinate irrigation, logistics, and quality assurance in real time, adjusting automatically to changing conditions.

3.2.4 POSITIONING FOR THE VEGETABLE INDUSTRY

The Australian vegetable industry already experiences the benefits of narrow AI through precision agriculture and service-based tools.

The emergence of generative AI now opens the door for growers themselves to engage directly with AI, using it as part of daily operations, creating a unique moment to build confidence, capability, and relevance.

Agentic AI remains a longer-term opportunity, requiring robust data integration, interoperability standards, and governance frameworks.

By focusing industry investment on generative AI today, the vegetable sector can establish the necessary foundations, including skills, data, and trust, needed to transition towards more autonomous systems in the future. This project has recognised the evolving nature of the AI landscape and, while not ignoring existing narrow AI applications or the emerging "blue-sky" research opportunities in agentic AI, it has focused deliberately on the present. The emphasis has been on exploring how currently available tools and models, particularly generative AI, can be applied in practical, grower-led contexts to support efficiency, compliance, and informed decision-making across the vegetable industry.

3.3 GLOBAL TRENDS IN AGRICULTURAL AI

The evolution of AI, as described, is reflected globally, where both public and private investment are accelerating the shift from experimental to mainstream use in agriculture. Governments, research institutions, and technology companies are increasingly collaborating to embed AI into the food system, from data analytics and logistics to on-farm automation and crop forecasting.

While early adoption was led by large-scale commodity sectors, horticulture is now emerging as a significant focus area. Advances in computer vision, robotics, and generative systems are being applied to high-value crops where quality, labour, and sustainability drivers make automation particularly attractive.

Key global trends of note include:

- **Rapid capital growth:** More than US $200 billion has been invested in agtech over the past decade, with AI now the fastest-growing category of that spend[1]
- **Commercial concentration:** North America currently represents almost half of global revenue from AI-based agriculture, followed by Europe and East Asia[2]
- **Government support:** Countries such as the United States, the Netherlands, Japan, and Israel have established public–private innovation hubs to accelerate on-farm automation and AI integration[3]
- **Technology emphasis:** Narrow AI applications, especially computer vision and predictive analytics, still dominate commercial deployment, while generative AI and agentic AI remain in early adoption or research stages.[4]

Together, these trends indicate a clear global trajectory of agriculture moving from discrete, task-specific AI systems toward more connected, adaptive, and decision-support-oriented models. This provides a useful benchmark for the Australian vegetable industry, which is well positioned to adapt global lessons to local conditions.

3.3.1 INTERNATIONAL EXAMPLES OF AI IN VEGETABLE PRODUCTION

To illustrate these global trends in practice, Table 3-1 summarises selected examples of AI applications across vegetable and horticultural production systems.

These examples show how different forms of AI, from narrow to generative, are being applied internationally, and the potential lessons and opportunities for Australian growers.

Table 3-1: Examples of international AI applications in vegetable and horticultural production

Application area	International example	Status / maturity	Relevance to Australian vegetable industry
Business management	AI-enabled compliance and record-keeping systems used by the US fresh-produce sector[5]	Commercial deployment	High – directly applicable for reducing audit and reporting burden, aligning with grower interest in QA automation.
Greenhouse and controlled environments	Digital-twin systems for greenhouse vegetables in the Netherlands and Spain[6]	Pilot to early commercial	Moderate – potential for protected-cropping enterprises once local data integration improves.
Crop and pest monitoring	Computer-vision and predictive-analytics models for pest and disease detection (EU research programs)[7]	Pilot / research	High – applicable to open-field vegetables; adaptation to Australian crops underway via ARC Research Hub (Griffith University).

1 Precedence Research (2025). “Artificial Intelligence (AI) in Agriculture Market Size, Share, and Trends Report 2025–2034.”
2 Precedence Research (2025). “Generative AI in Agriculture Market – Regional Analysis.”
3 OECD (2024). “AI and Digital Transformation in Agriculture: Policy Experiences from Leading Economies.”
4 University of Technology Sydney (2025). “AI is Coming for Agriculture, but Farmers Aren’t Convinced.”; AgFunder (2024) AgriFood Tech Investment Report.
5 IBM Food Trust (2023) AI-enabled compliance and traceability for the US produce industry; Trimble Agriculture (2024) Connected Farm Compliance Solutions; US FDA (2024) FSMA Produce Safety Rule Implementation Update.
6 Wageningen University & Research (2024) Digital Twin Greenhouse Project; European Commission (2023) SmartAgriHubs Project Summaries.
7 European Union (2024) DEMETER: Smart Agriculture and AI Integration in Crop Protection; EUPHRESCO Network (2023) AI-Based Pest Forecasting Models for Horticulture.

Application area	International example	Status / maturity	Relevance to Australian vegetable industry
Post-harvest grading and QA	Vision-based grading in packhouses across the US and EU horticulture industries[8]	Commercial adoption	High – proven labour savings and product consistency; compatible with Australian packhouse operations.
Autonomous field robotics	SwarmFarm (Australia) and Muddy Machines (UK) weeding and harvesting robots[9]	Commercial / trials	High – already active in Australia through GOFAR and DAF mechanisation programs.
Generative AI advisory systems	Microsoft Research "Virtual Agronomist" chatbots (Brazil, India, USA)[10]	Early commercial pilots	Emerging – opportunity to localise for Australian vegetables with region-specific data.
AI for seed and variety selection	Syngenta + Heritable Agriculture predictive genomics platform[11]	Research / pre-commercial	Medium – potential for future adaptation to variety selection in Australian micro-climates.

3.4 AUSTRALIAN MARKET POSITION

Australia has a strong foundation for AI adoption in the vegetable sector, built on leading research capability, progressive grower networks, and an increasingly active agtech sector.

National programs such as the ARC Research Hub for AI in Farming (Griffith University), the Queensland DAF Gatton Smart Farm, and CSIRO's MAGDA++ initiative are driving advances in automation, robotics, and data analytics. Together, these initiatives provide the technical infrastructure and expertise needed to trial and refine AI applications in real production systems.[12]

Commercial maturity is also advancing rapidly. More than 50 Australian companies now offer AI-enabled products and services spanning sensing, robotics, logistics, and supply-chain optimisation. These include start-ups and established providers delivering solutions such as vision-based quality assurance, precision irrigation scheduling, and predictive analytics for harvest timing.[13]

Hort Innovation and state-government co-investment programs, such as the A$4.1 million Hort Innovation and Queensland DAF mechanisation initiative and the A$5 million ARC Research Hub, are accelerating development and on-farm demonstration of AI-based tools.[14] These programs are creating the essential test beds for future AI adoption and helping to de-risk investment through collaborative pilots.

Despite this strong technical capacity, adoption within the vegetable industry remains limited. Growers continue to identify uncertainty about relevance, data trust, and cost as primary barriers. In many cases, available AI systems have not yet been tailored to vegetable production systems or integrated with existing farm-management software. Addressing these challenges requires evidence of practical value and a consistent framework for assessing technologies.

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8 TOMRA Food (2024) AI-Driven Optical Sorting Solutions; Compac InVision System (2023); European Fruit Sorting Automation Project (2023).

9 SwarmFarm Robotics (2024) Autonomous Weeding and Spraying Systems; Muddy Machines Ltd (2024) Selective Harvesting Robots; Queensland DAF (2024) Horticulture Mechanisation Program.

10 Microsoft Research (2024) AI4Agriculture: Virtual Agronomist Pilot Program; FarmBeats Project Brief (2023).

11 Syngenta Group (2024) AI Collaboration with Heritable Agriculture for Predictive Genomics (Press Release, April 2024).

12 ARC Research Hub for AI in Farming (2025) Project Overview. Griffith University; Queensland DAF (2024) Gatton Smart Farm Program Summary; CSIRO (2024) MAGDA++ – Machine-Assisted Global Decision Analytics.

13 AgriFutures (2024) Australian Agtech Companies Database; AgFunder (2024) AgriFood Tech Investment Report.

14 Hort Innovation & Queensland DAF (2024) Mechanisation and Automation in Horticulture Program; ARC (2025) Research Hub for AI in Farming Funding Announcement.

4 Industry Consultation Findings

4.1 OVERVIEW

Industry consultation formed the cornerstone of the VG24008 project.

Through regional workshops (Victoria, Western Australia and Queensland), Strategic Investment Advisory Panel (SIAP) presentations and a national online webinar, the project engaged vegetable growers, supply-chain partners, and extension specialists to test perceptions of AI, explore practical use cases, and identify barriers and enablers to adoption.

The consultation process was designed to move beyond general discussion and ground the conversation in real, on-farm contexts. Each session combined short demonstrations of AI tools with structured dialogue to capture grower perspectives on where AI could add tangible value across production, post-harvest, and business management functions.

This section summarises the key messages heard through these consultations. While direct experience with AI tools remains limited, interest grows rapidly once growers are exposed to relevant, practical examples. Participants consistently emphasised that successful AI adoption in the vegetable industry will depend on clarity of value, trust in data use, and evidence of measurable time or cost savings.

4.2 KEY THEMES FROM GROWER AND INDUSTRY ENGAGEMENT

Across the regional workshops and industry consultations, participants expressed a shared curiosity about AI and a desire for clear, practical examples of how it could enhance vegetable production and business management.

Despite different production systems and digital capability levels, common messages emerged around four key areas:

1. Awareness and confidence
2. Priority applications
3. Barriers to adoption
4. Enablers for success.

4.2.1 AWARENESS AND CONFIDENCE

Participants generally started from a low base of AI knowledge, but interest grew rapidly once they could see relatable, on-farm examples. Demonstrations were consistently described as the turning point, helping translate abstract technology into something tangible and useful.

Key insights included:

- **Low starting awareness**: Few participants reported using AI tools in their current operations
- **High interest once exposed**: Live demonstrations proved particularly effective in building curiosity and confidence
- **Hands-on learning preferred**: Growers indicated a preference for applied, example-based training rather than theoretical presentations
- **Trust and simplicity critical**: Participants valued transparency and control over data and were cautious about subscription models or “black-box” tools.

4.2.2 PRIORITY APPLICATION AREAS

While participants recognised AI's broad potential, they consistently identified *immediate and near-term* opportunities in areas where the technology can directly address existing pain points, especially administrative burden, labour management, and resource efficiency.

The opportunities identified were clustered around four domains:

Business and workforce management

- AI-assisted compliance documentation and audit preparation
- Multilingual induction and safety training for diverse workforces
- Automated meeting minutes, action lists, and reporting templates.

Production and post-harvest

- Predictive maintenance of machinery and irrigation systems
- Crop forecasting and scheduling
- Vision-based quality assurance in packing lines.

Grower-led innovation

- Expanding the Open Weed Locator (OWL) model to other crops and regions
- Creating shared libraries of prompts, images, and training data relevant to Australian vegetables.

Extension and communication

- Using AI to streamline regional reporting and milestone tracking within VegNET or similar national, complex extension programs
- Supporting Regional Development Officers with AI-enabled resource development and translation tools.

An observation of these priorities emerging from the grower consultation indicate that growers see AI as a way to simplify existing processes, before tackling more complex production-level automation.

4.2.3 BARRIERS TO ADOPTION

Across all consultations, participants highlighted remarkably consistent challenges limiting adoption as outlined in Table 4-1.

While these barriers vary in importance by region, they collectively reflect systemic issues of digital access, integration, and trust.

A key finding in relation to barriers was participant identification that without clearer interoperability standards and accessible training, many AI systems risk remaining underutilised regardless of their technical sophistication.

Table 4-1: Identified barriers to adoption

Barrier	Description / Example
Connectivity	Limited broadband or mobile coverage restricts access to cloud-based systems.
Trust and data ownership	Concerns about who owns data entered into AI systems and how it may be used commercially.
Cost and subscription fatigue	Many businesses already manage multiple software subscriptions; preference for integrated or open-source options.

Barrier	Description / Example
Digital literacy	Variation in staff skills and comfort with technology.
Scam awareness	Specific concerns raised in Queensland about scams or false claims around "AI tools".
Integration and interoperability	Growers noted frustration with platforms that do not communicate or duplicate data entry.

4.2.4 ENABLERS AND SUCCESS FACTORS

Alongside the barriers, growers and industry representatives identified several factors that would build confidence and accelerate safe adoption. Most emphasised that trust and visible benefit, not application novelty, will drive engagement.

Key enablers identified to support adoption included:

- **Peer-led demonstrations**: Growers trust other growers more than technology vendors
- **Visible ROI**: Demonstrating measurable time or cost savings is the strongest motivator for adoption
- **Open-source collaboration**: Initiatives such as OWL are seen as transparent and locally relevant
- **Partnerships with existing programs**: Leveraging established extension platforms (e.g. Soil Wealth ICP, VegNET) provides trusted delivery channels.

4.3 REGIONAL INSIGHTS

While the key themes were consistent nationally, regional engagement revealed nuanced perspectives shaped by farm size, crop type, and the maturity of local digital infrastructure. The following summaries highlight these distinctions and illustrate how regional priorities inform the broader national picture of AI readiness across the vegetable industry.

4.3.1 MELBOURNE, VICTORIA

Participants emphasised administration and compliance as major time burdens. AI was viewed as a practical tool to simplify audits, workforce inductions, and documentation. Generative AI demonstrations, particularly for real-time text generation and translation, were well received for their immediate relevance to business operations.

4.3.2 MANJIMUP, WESTERN AUSTRALIA

Connectivity and system fragmentation were identified as the most significant barriers. The Open Weed Locator (OWL) project generated strong discussion as a model for open, community-driven innovation. Participants advocated for regional demonstration sites to showcase applied AI in action and strengthen peer-to-peer learning.

4.3.3 BUNDABERG, QUEENSLAND

Engagement was high among medium- to large-scale enterprises already experienced with mechanisation and precision agriculture. Participants were particularly interested in predictive analytics for irrigation scheduling and yield forecasting but raised concerns about data trust and online "AI" product scams.

Together, these regional perspectives confirmed that while the industry's starting point varies, growers across all regions shared a clear appetite for practical demonstrations, trusted delivery partners, and tools that deliver measurable efficiency gains.

4.4 CROSS-SECTOR ALIGNMENT AND INTEGRATION OPPORTUNITIES

Consultation highlighted that the vegetable industry is not starting from scratch. Many levy-funded programs and national initiatives already provide trusted platforms that can be leveraged to build AI capability and scale adoption efficiently. Rather than creating new, standalone efforts, stakeholders saw the greatest potential in embedding AI literacy and simple, practical tools within existing networks and demonstration programs.

Identified key alignment opportunities through the consultation included:

- **VegNET Phase 4 (2026–2030):** Opportunity to embed AI literacy and simple workflow tools within regional extension delivery, supported by targeted training for Regional Development Officers
- **Soil Wealth ICP:** An established and trusted model for practice-change based extension, offering a strong platform to integrate AI applications and build grower capability through practical, systems-based learning
- **Gatton Smart Farm and GOFAR programs:** Established platforms for demonstrating applied AI in automation, weeding, and disease monitoring under real production conditions
- **AusAgritech and SproutX:** Identified as key partners for commercialisation support, start-up acceleration, and AI entrepreneur mentoring across the wider horticulture and agtech ecosystem.

4.5 SUMMARY OF FINDINGS

Consultation across all workshops, SIAP sessions, and partner discussions confirmed a strong appetite for AI in the vegetable industry, but also a cautious and pragmatic outlook. Growers want to see solutions that fit within existing business systems, save time, and reduce administrative load before committing to more complex applications.

A summary of the main insights from the consultation include:

1. **Awareness is low, but interest is high** once growers experience relevant, hands-on demonstrations
2. **The most immediate opportunities** are in business management and compliance rather than production automation
3. **Capability building and confidence** are essential precursors to adoption and should precede large-scale investment
4. **Peer-led, example-based learning** is preferred over theoretical or highly technical training
5. **Integration with existing programs** such as VegNET and Soil Wealth ICP provides a low-risk, high-trust pathway for industry-wide engagement.

These findings emphasise the industry's appetite for a **"confidence-first" approach**, focusing on practical exposure, incremental adoption, and demonstrable value rather than speculative or large-scale technology investment.

5 AI Feasibility and Readiness Assessment

5.1 PURPOSE AND APPROACH

The feasibility assessment formed the analytical foundation of this project, evaluating how different types of AI could deliver practical, measurable benefits to the Australian vegetable industry.

It complements the consultation findings and informed the roadmap presented in Section 6 by identifying which AI technologies are ready for adoption, which require piloting, and which should be monitored for future potential.

A total of 27 AI technologies and applications relevant to vegetable production, post-harvest processing, and business management were reviewed. These ranged from generative AI and computer-vision tools to robotics, digital twins, and integrated forecasting platforms. Each technology was assessed against a structured framework that considered both technical and adoption readiness.

The purpose of the assessment was to:

- Provide a consistent, evidence-based method for comparing AI technologies across maturity levels and use cases
- Identify high-potential applications that align with grower priorities and industry needs
- Inform investment and extension priorities under the staged adoption roadmap
- Highlight capability and data gaps that may constrain wider adoption.

Evaluation criteria were developed collaboratively by RMCG and ARAIN, drawing on consultation insights, international benchmarking, and existing RDC frameworks for innovation readiness.

Further detail on the evaluation framework and findings is provided in the following sub-sections, with the full assessment available in Appendix 1.

5.2 FRAMEWORK AND EVALUATION CRITERIA

A structured evaluation framework was developed to assess the technical, commercial, and adoption feasibility of AI technologies within the vegetable industry.

The framework reflects the industry's need for practical, evidence-based tools that can be integrated into existing systems while minimising complexity and risk.

Each AI technology was evaluated against four core dimensions and grouped into one of three adoption pathways.

5.2.1 ASSESSMENT DIMENSIONS

Four assessment dimensions were selected to balance technical analysis with practical industry relevance. Each dimension reflects a key factor influencing whether and how AI technologies can be successfully adopted by vegetable growers. Together, they provide a consistent lens for comparing technologies that vary widely in purpose, maturity, and implementation complexity.

The framework draws from established technology-readiness and innovation-adoption models but was refined through industry consultation to ensure it reflected on-farm realities, such as connectivity, cost sensitivity, and integration with existing business systems. This approach enabled both a qualitative and quantitative assessment of feasibility, ensuring that recommendations were grounded in what growers can realistically use and sustain.

The four assessment dimensions for the feasibility assessment included:

6. AI Type Classification

Understanding the type of AI was essential to setting realistic expectations about performance, complexity, and timelines for adoption.

Three major categories were assessed:

- **Narrow AI (Task-Specific)**: Performs clearly defined tasks using machine learning, computer vision, or predictive analytics. Examples include disease detection, weeding, and yield forecasting
- **Generative AI (Content Creation)**: Produces new content, such as text, images, or summaries, based on existing data. Examples include compliance report generation, translation tools, and agronomy advisors
- **Agentic AI (Autonomous Decision-Making)**: Integrates multiple systems and data sources to make independent operational decisions (e.g. autonomous farm or robotic harvesting). These remain largely pre-commercial but represent the next frontier for innovation.

7. Commercial Readiness

Readiness levels indicate the extent of deployment, evidence base, and technical reliability:

- **Low:** Research or prototype stage; requires further validation before commercial use.
- **Medium:** Active pilots or early commercial releases; strong technical promise but limited integration experience
- **High:** Commercially available and proven under field conditions; multiple vendors and validated ROI

8. Adoption Complexity

Complexity was assessed based on infrastructure, integration, and skill requirements:

- **Low**: Plug-and-play tools; minimal training or infrastructure change
- **Medium**: Requires moderate investment or data integration; some training required
- **High**: Significant infrastructure, connectivity, or process redesign needed.

9. Implementation Cost

Estimated total cost of adoption, including set-up and annual operating expenses, was considered in three bands:

- **Low (<$10K):** Accessible to most businesses
- **Medium ($10K–$50K):** Suitable for larger enterprises or service-model delivery
- **High (>$50K):** Capital intensive; viable only for large operations or shared demonstration models.

5.2.2 ADOPTION CATEGORIES

Each technology was classified into one of three adoption pathways reflecting current feasibility and investment priority:

- **Adopt Now**: Readily deployable solutions with demonstrated performance and value (e.g. supply-chain AI analytics, IoT sensors, generative AI for documentation)
- **Pilot/Trial**: High-potential technologies requiring local validation and integration support (e.g. disease detection, autonomous weeding, generative AI advisors)
- **Monitor**: Longer-term or higher-complexity innovations that warrant continued observation and research investment (e.g. digital twins, autonomous multi-task robotics).

5.3 INSIGHTS BY ADOPTION CATEGORY

The feasibility assessment grouped 27 AI technologies into three adoption categories; Adopt Now, Pilot/Trial, and Monitor, based on commercial readiness, complexity, and integration potential.

Each category reflects a different stage of opportunity and investment focus, corresponding to the industry's three adoption horizons. The following sections summarise the characteristics and implications of each group.

5.3.1 ADOPT NOW – PROVEN AND ACCESSIBLE

These technologies represent the most immediately deployable AI solutions identified through the feasibility assessment. They align with existing digital capability across the vegetable industry and offer practical entry points for growers seeking to trial AI without major investment or system change.

Building on strong commercial evidence and user familiarity, these tools can help the industry move from awareness to confident use, particularly in business management, resource optimisation, and compliance reporting.

"Adopt Now" technologies are commercially available tools that have demonstrated performance and reliability under practical farm or supply-chain conditions. They are typically low-complexity, low-cost systems that require minimal integration effort, making them suitable for immediate use by individual businesses or through regional demonstration sites.

Typical characteristics:

- Low infrastructure requirements and user-friendly interfaces
- Proven time or cost savings within 6–12 months of implementation
- Suitable for delivery through extension and peer-to-peer training networks.

Representative technologies:

- Generative AI tools for compliance, documentation, and translation
- AI-enabled supply-chain optimisation and market forecasting systems
- IoT-linked predictive irrigation and resource-management platforms.

Industry implications:

Adoption of these tools can deliver early wins in administrative efficiency and decision support, helping to normalise AI use across the sector and build confidence for later, more complex applications.

5.3.2 PILOT / TRIAL – EMERGING WITH HIGH POTENTIAL

Technologies in this category represent the next wave of opportunity for the vegetable industry, solutions that are technically advanced and highly relevant, but not yet proven at commercial scale under Australian conditions.

The feasibility assessment found that these tools consistently attracted grower interest and supplier engagement but require structured testing to confirm reliability, integration, and value. Coordinated pilot programs will therefore play a pivotal role in bridging the gap between promising prototypes and practical, on-farm adoption.

The largest group of technologies fall into the "Pilot/Trial" category. These tools show strong technical potential but require field validation, integration testing, and evidence of ROI under Australian production conditions.

This group aligns directly with Horizon 2 – Applied Pilots, where structured, grower-led trials will generate practical evidence to guide adoption.

Typical characteristics:

- Medium readiness and complexity; already proven in research or protected environments
- High relevance to vegetable production but requiring adaptation for local data and workflows
- Strong interest from both technology providers and growers for collaboration.

Representative technologies:

- AI disease-detection systems (computer vision)
- Generative AI agronomy advisors for decision support
- Vision-based quality assurance and grading systems
- Autonomous and precision weeding platforms
- AI for seed and variety selection tailored to micro-climates.

Industry implications:

Targeted pilot programs will be critical to quantify benefits, validate technical claims, and inform the design of commercial service models. These pilots also serve as a training platform for growers and advisers to build applied AI skills.

5.3.3 MONITOR – FUTURE SYSTEMS

This category captures technologies at the frontier of agricultural innovation, advanced AI systems that are conceptually proven but not yet commercially viable within open-field vegetable production.

While these tools remain in development, they signal where the next generation of digital agriculture is heading, particularly toward autonomous operations, adaptive decision-making, and system-wide optimisation.

Monitoring these developments will help the vegetable industry stay strategically aligned with global innovation trends and ensure that future investment in research, data standards, and interoperability frameworks supports safe, scalable adoption.

Technologies classified as “Monitor” represent advanced or emerging AI systems that remain in research or early-prototype stages.

While they are not yet commercially feasible, these innovations provide important signals about the industry’s longer-term direction and areas for strategic investment under Horizon 3 – Systems and Trust.

Typical characteristics:

- High technical complexity and infrastructure dependency
- Require multi-system integration, advanced sensors, and continuous data feedback loops
- Offer potential for transformative efficiency once supporting frameworks are established.

Representative technologies:

- Digital-twin farm models integrating sensor, weather, and crop-growth data
- Fully autonomous multi-task robotic systems for planting, harvesting, and spraying
- Agentic AI systems capable of adaptive decision-making across production and logistics networks.

Industry implications:

Continued research and cross-sector collaboration will ensure Australia remains positioned to capitalise on these innovations as data standards, connectivity, and governance systems mature.

Investment during this phase should focus on interoperability, ethics, and validation frameworks that prepare the ground for safe adoption.

5.4 SUMMARY OF FINDINGS

The feasibility assessment confirmed that AI technologies relevant to the Australian vegetable industry vary widely in maturity, cost, and ease of adoption.

Of the 27 technologies reviewed, most fell within the medium readiness range, demonstrating strong potential but requiring targeted testing, validation, or adaptation to local conditions before broad industry rollout.

Overall classification outcomes were:

- **9 technologies** rated as **Adopt Now** – commercially available and immediately usable within existing production or business systems
- **11 technologies** rated as **Pilot/Trial** – high potential for productivity or efficiency gains but requiring on-farm validation or integration support
- **7 technologies** rated as **Monitor** – longer-term or complex applications that remain in early development phases.

The assessment covered a broad portfolio of applications, summarised in Table 5-1.

Table 5-1: Summary of AI technologies assessed through Feasibility Assessment

Functional Domain	Example Technologies	Primary AI Type	Readiness Range
Production	AI disease detection, crop forecasting, precision irrigation, autonomous weeding	Narrow / Agentic	Pilot–Monitor
Post-Harvest	Vision-based grading, defect detection, supply-chain analytics	Narrow	Adopt–Pilot
Business Management	Generative AI for compliance, translation, scheduling, predictive logistics	Generative / Narrow	Adopt–Pilot

These technologies collectively illustrate that while Australia's vegetable industry has access to credible, commercially relevant AI solutions, scaling their use will depend on targeted pilots, data integration, and user training.

5.4.1 KEY OBSERVATIONS ACROSS THE PORTFOLIO

Analysis of the 27 technologies assessed through the feasibility framework revealed several cross-cutting trends that highlight both the maturity and constraints of AI within the vegetable industry. While individual technologies vary widely in function and readiness, common themes emerged around accessibility, integration, and evidence. These observations provide an important context for interpreting the results and for prioritising future investment, particularly in aligning short-term adoption with long-term system development, which includes:

- **Strong near-term opportunity in Generative and Narrow AI:** Tools that automate information processing, such as compliance reporting, crop scheduling, or quality assurance, are both accessible and high-impact. Generative AI, in particular, offers low-cost entry points that can build grower confidence.

- **Barriers remain in interoperability and integration:** Many AI systems operate as standalone tools, leading to "subscription fatigue" and data fragmentation. Industry investment in connectors and data standards will be essential to unlock full value.
- **Evidence gap for advanced systems:** While international case studies show promise for digital twins and autonomous robotics, few applications have been validated in open-field vegetable systems under Australian conditions.
- **Return on investment depends on usability:** Growers are more likely to adopt AI when the value proposition is immediate and tangible, saving time on documentation, improving labour scheduling, or reducing input waste.

5.5 IMPLICATIONS FOR INDUSTRY AND INVESTMENT

The feasibility assessment demonstrates that AI adoption in the vegetable sector will not follow a single trajectory. Early wins will come from accessible, generative tools that build capability and confidence, while medium to long-term investments should target interoperability, governance, and cross-sector collaboration.

The feasibility assessment identified **five priority AI applications** for near-term piloting under *Horizon 2* (Section 6.2):

1. AI disease detection systems
2. Generative AI agronomy advisors
3. Autonomous and precision weeding systems
4. Vision-based quality assurance and grading
5. AI for seed and variety selection.

Together, these represent a balanced portfolio of narrow and generative AI tools that are technically mature enough for applied testing, but still require contextual adaptation for Australian vegetable production systems.

The findings validate the project's "confidence-first" approach: building foundational understanding and low-risk experience before scaling to complex, system-level innovation. Continued benchmarking, pilot investment, and data standardisation will be essential to sustain momentum and position Australia's vegetable industry as a leader in responsible AI adoption.

6 Implementation Roadmap

The consultation process confirmed that while vegetable growers are curious about AI, adoption will depend on clarity of value, trust, and confidence. Growers want to see practical examples that save time, reduce costs, or simplify compliance before investing in more complex or large-scale systems. Building capability and demonstrating value therefore need to occur in tandem with technology development.

This section presents a twelve-point roadmap for AI adoption in the Australian vegetable industry, structured across three horizons that reflect increasing levels of capability, maturity, and integration. The roadmap provides a practical sequence of actions designed to move the industry from initial awareness to confident, widespread use of AI.

The approach is underpinned by a **"confidence-first" model**. Rather than focusing immediately on automation or advanced data integration, it prioritises helping growers understand, test, and trust AI in their existing operations, while outlining clear pathways for future investment. This reflects the consistent message from consultation and SIAP discussions that capability, confidence, and practical relevance must precede major technology investment.

To guide industry planning and investment, three horizons are identified and discussed:

- **Horizon 1 - Capability and Confidence**: including establishing the foundations for AI adoption through awareness, training, and peer-to-peer learning
- **Horizon 2 - Applied Pilots**: that supports practical, grower-led pilots that demonstrate measurable value and build shared evidence of what works
- **Horizon 3 - Systems and Trust**: which develops the frameworks, standards, and governance needed to integrate AI safely and effectively across the sector.

Each horizon represents a step in maturity rather than a fixed timeframe, recognising that businesses and regions will progress at different speeds depending on readiness and opportunity. This forms a structured and achievable roadmap for embedding AI capability within the vegetable industry, starting with confidence and building towards coordinated, system-level integration.

6.1 HORIZON 1 – CAPABILITY AND CONFIDENCE

The first horizon focuses on building the capability, confidence, and curiosity needed for meaningful AI adoption.

Consultation confirmed that awareness remains low, but enthusiasm increases rapidly when growers can see AI tools in action and relate them to their own operations. Early investment in skills, exposure, and trusted information is therefore essential to create the foundation for long-term adoption.

AI should first be positioned as an enabler, a practical tool that simplifies daily tasks rather than a replacement for people or processes. By embedding AI literacy within existing extension, training, and communication programs, the industry can normalise its use, reduce apprehension, and establish a shared understanding of what "good AI" looks like in a farm business context.

Key actions under this horizon include:

- Develop tailored AI training and awareness programs for growers, advisors, and Regional Development Officers (RDOs), delivered through trusted levy-funded initiatives such as VegNET Phase 4 (2026–2030)

- Integrate AI literacy into existing extension frameworks such as Soil Wealth ICP, focusing on how AI can support data analysis, communication, and decision-making in day-to-day operations
- Create clear, example-based communication materials that demonstrate practical applications, including video explainers, prompt libraries, and "how-to" guides
- Promote a culture of safe experimentation by encouraging use of low-cost, accessible AI tools (e.g. generative AI for documentation, translation, or meeting notes)
- Embed AI awareness and safety, including privacy, scam detection, and data ethics, into all extension and training resources
- Support open, community-driven innovation, such as collaborative prompt libraries or grower-built tools, to encourage shared learning and transparency.

The emphasis at this stage is on **learning by doing,** helping growers gain direct, low-risk experience with AI that builds familiarity and trust.

This "capability-first" approach is anticipated to ensure that as more advanced technologies become available, growers already have the understanding and confidence to evaluate and adopt them.

CASE STUDY: OPEN WEED LOCATOR (OWL)

The **Open Weed Locator (OWL)** demonstrates the power of open, collaborative AI innovation driven by growers themselves. Originally developed as a low-cost, open-source weed detection tool, OWL uses computer vision and machine learning to identify weeds in real time.

Its development involved collaboration between Western Australian growers as part of the Warren Cauliflower Improvement Group, researchers and regional innovation hubs, ensuring the system remained accessible and adaptable to local needs.

OWL illustrates how AI can be applied pragmatically, addressing a real production challenge while remaining transparent and farmer-owned.

Its success underscores the value of starting small, sharing openly, and empowering growers to participate directly in AI development rather than relying solely on commercial platforms.

6.2 HORIZON 2 – APPLIED PILOTS

With capability and confidence increasing, the next horizon focuses on application, including testing and validating AI tools through practical, grower-led pilots.

Consultation and SIAP feedback consistently emphasised the need to "see it working" before widespread adoption can occur. Applied pilots provide this bridge, turning interest into evidence and building a shared understanding of what delivers real value on-farm.

These pilots should be co-designed with growers, researchers, and technology partners to ensure relevance and credibility. They also offer a mechanism for aligning innovation with the industry's core priorities, including labour efficiency, input management, compliance, and sustainability. By collecting performance data under commercial conditions, pilot programs can demonstrate return on investment and refine AI solutions before larger-scale rollout.

Key actions under this horizon include:

- Establish a national AI Pilot Program for horticulture, delivered through Hort Innovation in partnership with other RDCs, VegNET, and state agencies

- Demonstrate and validate priority AI applications identified through this project, focusing on practical field and business pilots that generate measurable value and build confidence. Priority early piloting include:
  - **AI disease detection systems** – validating accuracy and workflow integration for key vegetable crops under Australian conditions
  - **Generative AI agronomist advisors** – improving context accuracy, trust, and usability for on-farm decision support
  - **Autonomous and precision weeding systems** – testing service-based robotic platforms for reliability and cost-effectiveness
  - **Vision-based grading and quality assurance** – assessing value in packhouses and post-harvest automation
  - **AI for seed and variety selection** – piloting predictive tools for matching genetics to microclimates and production systems
- Co-design pilots with participating growers to ensure usability and integration with existing systems
- Apply consistent evaluation metrics, such as time saved, error reduction, cost efficiency, and data trust, to assess both commercial and social value
- Document and communicate pilot learnings through VegNET and partner networks to support peer-to-peer extension
- Leverage existing demonstration sites such as Gatton Smart Farm and the GOFAR network for testing AI in automation, weeding, and disease monitoring.

The aim is to develop a **credible evidence base,** showing where AI delivers measurable benefit and where further development is needed.

Pilots also serve as “learning laboratories” for digital extension, building capability among growers, advisors, and service providers alike.

CASE STUDY: AGWORLD ALMA – GENERATIVE AI FOR FARM SUPPORT

Agworld Alma represents one of the first commercial applications of **generative AI** in Australian agriculture.

Using a secure language model trained on agronomic and farm-management data, Alma assists users to generate field notes, compliance records, and agronomic summaries in plain language.

Early trials indicate significant time savings in record-keeping and audit preparation, especially for vegetable businesses with complex supply-chain documentation.

The tool demonstrates how generative AI can complement existing platforms, simplifying administration while maintaining data integrity and user control.

6.3 HORIZON 3 – SYSTEMS AND TRUST

As capability and pilot experience grow, the next horizon focuses on establishing the systems, standards, and governance that will enable AI to be integrated safely, ethically, and at scale across the vegetable industry.

Growers made clear that trust in data, platforms, and institutions is a prerequisite for adoption. Without confidence in how information is used or verified, even technically sound AI tools will struggle to gain traction.

This horizon therefore shifts attention from individual applications to the broader ecosystem conditions that support long-term AI use.

It recognises that reliable, transparent systems build the social licence and interoperability needed for AI to deliver sustained value.

Key actions under this horizon include:

- Develop national interoperability and data-sharing standards in partnership with other RDCs, the Department of Agriculture, Fisheries and Forestry (DAFF), and industry data councils to reduce duplication and enable seamless communication between platforms
- Establish validation and auditability pipelines to verify AI outputs and ensure transparency in decision-making processes
- Embed privacy, ethical, and cyber-safety frameworks within all industry-facing AI programs, ensuring compliance with emerging national AI governance standards
- Invest in trusted data infrastructure, such as secure, anonymised data lakes or federated systems that allow benchmarking without compromising privacy
- Foster cross-sector collaboration between horticulture, livestock, and grains industries to align on common data formats, workforce capability standards, and responsible AI principles
- Support advanced applications (e.g. digital twins, integrated forecasting, and autonomous systems) through targeted R&D once foundational capability and governance structures are in place.

These actions collectively aim to position the vegetable industry within a **coordinated, cross-sector AI ecosystem,** one that maintains grower ownership of data while enabling system-level innovation and efficiency.

CASE STUDY: DIGITAL-TWIN GREENHOUSE SYSTEMS

International research led by Wageningen University & Research and partners in Spain demonstrates the potential of digital-twin systems for protected cropping.

These AI-driven models replicate real greenhouse environments in virtual space, continuously analysing climate, irrigation, and crop-growth data to optimise management decisions in real time.

While still in early commercial stages, digital-twin applications illustrate what is possible when strong data integration and interoperability frameworks are in place.

Adapting such systems for Australian protected cropping would require standardised data pipelines, trusted sensor networks, and transparent governance.

7 Conclusions and Recommendations

7.1 CONCLUSIONS

The *Exploring AI Applications for the Vegetable Industry (VG24008)* project has delivered a clear and evidence-based foundation for how artificial intelligence (AI) can be adopted to enhance productivity, efficiency, and sustainability within the Australian vegetable industry.

Through consultation, feasibility assessment, and practical framing, the project has helped move AI from concept to credible opportunity, grounded in grower needs, industry priorities, and realistic stages of readiness.

The project has delivered against its stated objectives, including:

- **Identifying high-impact opportunities**: Five priority applications were identified with strong potential to improve production efficiency, business management, and decision support, spanning disease detection, generative agronomy advice, autonomous weeding, vision-based grading, and seed and variety selection.
- **Assessing feasibility and readiness**: Twenty-seven AI technologies were systematically evaluated using a structured framework, classifying them by commercial readiness, adoption complexity, and implementation cost. This produced a transparent evidence base that supports informed investment decisions.
- **Developing a roadmap for adoption**: A three-horizon roadmap was designed to guide industry investment and implementation, linking capability building, applied pilots, and system-level integration into a cohesive national pathway.

7.2 RECOMMENDATIONS FOR A PATHWAY FORWARD

The findings from the project reaffirm that AI adoption in the vegetable industry will not occur through technology alone, it requires confidence, collaboration, and context.

The three-horizon roadmap outlined in this report provides a practical, scalable framework for future investment, namely:

- **Horizon 1 – Capability and Confidence** focuses on building awareness, literacy, and trust through training, demonstrations, and peer learning
- **Horizon 2 – Applied Pilots** enables grower-led validation of promising technologies to generate evidence of value
- **Horizon 3 – Systems and Trust** establishes the data standards, governance, and interoperability needed for safe, scalable integration.

Central to this approach is the “confidence-first” philosophy that has shaped the roadmap. Rather than beginning with high-cost automation or speculative technologies, the project has focused on building the foundations, skills, awareness, and relevance, necessary for enduring adoption. This staged, evidence-based model ensures that AI complements existing farm systems and delivers measurable benefit to growers.

A summary of the key focus, actions, and outcomes across the three horizons is presented in Table 7-1, illustrating how early investment in confidence and capability will enable safe, scalable adoption of AI over time.

Table 7-1: Recommendations for AI Adoption Horizons in the Australian Vegetable Industry

Horizon	Timing / Focus	Key Actions / Recommendations	Intended Outcomes
1. Capability & Confidence	*Now – 12 months* Build awareness, confidence and foundational skills across industry.	1. Invest in training and extension programs to increase grower exposure and confidence in AI 2. Support and fund peer-led demonstrations of generative AI for business support (minutes, compliance, workforce) 3. Integrate AI learning into VegNET Phase 4 and existing levy programs to build foundational skills (e.g. RDO/adviser training, regional workshops) 4. Publish a vegetable-specific use-case and prompt library, including privacy and scam-awareness guidance.	▪ Greater understanding and confidence among growers and advisers ▪ AI seen as a practical business tool, not a novelty ▪ Early adoption of low-risk, accessible applications.
2. Applied Pilots	*1 – 3 years* Demonstrate and validate AI solutions through practical, grower-led pilots.	5. Implement pilot projects to test and validate the five priority AI applications identified through the feasibility assessment: ▪ AI disease detection systems ▪ Generative AI agronomy advisors ▪ Autonomous and precision weeding ▪ Vision-based quality assurance ▪ AI for seed and variety selection. 6. Support and expand grower-led innovation initiatives (e.g. OWL) to scale open-source, locally relevant solutions with standardised evaluation frameworks 7. Test context-engineering approaches that adapt existing AI tools to farm-specific needs 8. Develop data interoperability standards and invest in connectors to reduce subscription fatigue and build trust.	▪ Evidence of ROI and practicality from on-farm pilots ▪ Refined solutions suited to vegetable production systems ▪ Shared learning network linking pilots, VegNET and research partners.
3. Systems & Trust	*3 – 5 + years* Establish governance, standards and infrastructure for safe, scalable AI.	9. Develop data-validation and auditability pipelines to improve trust in AI outputs 10. Support development of advanced applications (digital twins, integrated forecasting, precision robotics) 11. Embed scam-safety, privacy and verification guardrails into all industry-facing tools and training 12. Ensure scalability by embedding interoperability and context-engineering principles that allow businesses to tailor AI tools to their specific needs.	▪ Trusted, transparent data ecosystem ▪ Cross-industry alignment on responsible AI standards ▪ Enabling environment for long-term, system-level innovation.

Appendix 1: Detailed AI Feasibility Assessment

AI Technology Feasibility Assessment

Australian Vegetable Industry

October 2025

Prepared for Hort Innovation VG24008

Executive Summary

This feasibility assessment evaluates 27 AI-enabled technologies for Australian vegetable production using a structured multi-criteria framework. The analysis prioritizes AI-enabled integration within existing agtech systems rather than standalone AI deployment, recognizing that practical adoption requires AI to augment current farm operations.

Assessment Framework

Each technology is evaluated across four dimensions:

- **AI Type:** Narrow AI (specific tasks), Generative AI (content creation), or Agentic AI (autonomous decision-making)
- **Commercial Readiness:** High (proven, available now), Medium (pilots/trials), Low (research stage)
- **Adoption Complexity:** Low (simple integration), Medium (moderate change), High (significant infrastructure)
- **Implementation Cost:** Low (<$10K), Medium ($10K-$50K), High (>$50K)

Key Findings

Adopt Now (9 technologies): Proven ROI with low barriers - IoT sensor networks with AI analytics, satellite monitoring with machine learning, supply chain AI platforms, cloud-based irrigation optimization, and simple generative AI for business support. These technologies offer 6-18 month ROI with minimal complexity.

Pilot/Trial (11 technologies): Strong potential but requiring validation - AI disease detection systems (99% research accuracy), generative AI advisors for agronomic decisions (currently 80% accuracy), autonomous weeding robots, precision spraying systems, and post-harvest monitoring. These technologies need 2-3 years for mainstream viability through structured pilot programs.

Monitor (7 technologies): High potential but 3-5+ years from viability - automated harvesting systems, multi-task autonomous robots, fully integrated farm management AI, agentic AI decision-making systems, and blockchain traceability standards. These require continued research investment and cost reduction.

Strategic Implications

The assessment validates the staged adoption pathway proposed in the VG24008 discussion paper: building capacity and confidence with simple generative AI tools for business management (immediate), advancing to narrow AI for production support through pilots (2-3 years), and preparing infrastructure for agentic AI systems (3-5+ years). This progression aligns with international patterns where AI adoption is highest in business operations (compliance, quality assurance) while production-level automation remains at pilot stage.

Critical Success Factor: Low-cost generative AI for business management provides the confidence-building foundation necessary before advancing to higher-cost, higher-complexity production AI. The 9 'Adopt Now' technologies average $8,000 initial investment with 12-month ROI, creating accessible entry points that establish data infrastructure for future AI applications.

Investment Context: $9.1M in active government programs ($5M ARC Research Hub at Griffith University, $4.1M Hort Innovation + Queensland DAF + GOFAR mechanization program) demonstrates commitment to transitioning research to commercial deployment. Five detailed case studies illustrate practical implementation pathways across the readiness spectrum.

1. Multi-Criteria Assessment Framework

1.1 Framework Rationale

This assessment uses a structured multi-criteria framework to evaluate AI technologies for Australian vegetable production. The framework recognizes that successful AI adoption requires balancing technical capability, economic viability, and practical implementation complexity. Rather than evaluating standalone AI systems, the framework emphasizes AI-enabled integration within existing agtech infrastructure - recognizing that practical adoption requires AI to augment current farm operations, not replace them entirely.

1.2 Evaluation Criteria

AI Type Classification

Understanding the type of AI is critical for setting realistic expectations about capability, complexity, and timeline:

- **Narrow AI (Task-Specific):** Performs specific, well-defined tasks using machine learning, computer vision, or predictive analytics. Examples: disease detection, autonomous weeding, satellite crop monitoring. Advantages: proven accuracy, clear ROI, manageable complexity. Current state: 15+ technologies commercially available or in advanced trials.
- **Generative AI (Content Creation):** Creates new content (text, recommendations, reports) using large language models. Examples: agronomic advisors, compliance report generation, multilingual workforce inductions. Advantages: low cost, immediate deployment, high accessibility. Limitations: requires human verification (currently 80% accuracy), 'black box' concerns. Current state: 6 technologies in early commercial deployment.
- **Agentic AI (Autonomous Decision-Making):** Makes independent decisions across multiple systems with minimal human intervention. Examples: fully autonomous farms, integrated multi-task robots. Advantages: highest potential efficiency gains. Limitations: highest complexity, liability concerns, trust barriers, 3-5+ year timeline. Current state: 6 technologies in research/prototype stage.

Commercial Readiness Assessment

Readiness levels reflect actual deployment status and evidence base:

- **High:** Commercially available with proven track record. Multiple vendors operating in Australian market. Demonstrated ROI through case studies or peer-reviewed research. Minimal technical risk. Examples: IoT sensor networks, satellite monitoring, supply chain AI platforms.
- **Medium:** Pilots or trials underway with early commercial deployments. Academic validation strong (e.g., 99% disease detection accuracy) but integration challenges remain. 2-3 year timeline to mainstream adoption. Examples: AI disease detection (Fermata), generative AI advisors (Agworld Alma), autonomous weeding robots.
- **Low:** Research stage or early prototypes. Technical feasibility demonstrated but commercialization facing significant barriers (cost, reliability, integration). 3-5+ year timeline. Examples: automated harvesting, multi-task robots, fully autonomous farms.

Adoption Complexity Evaluation

Complexity reflects infrastructure requirements, training needs, and change management:

- **Low:** Minimal infrastructure changes. Simple integration with existing systems. Low training requirements. Can be adopted by individual growers without industry coordination. Examples: satellite monitoring, generative AI for business tasks, basic IoT sensors.

- **Medium:** Moderate infrastructure investment. Integration with 2-3 existing systems. Training and process changes required. May need connectivity improvements or data standardization. Examples: AI disease detection systems, irrigation optimization platforms, autonomous weeding.
- **High:** Significant infrastructure overhaul. Integration across multiple systems. Extensive training and organizational change. May require industry-wide standards or coordination. Examples: automated harvesting, multi-task robots, fully integrated farm management AI.

Implementation Cost Categories

Costs include initial capital, annual operating expenses, and integration:

- **Low (<$10K total):** Initial investment under $10,000 with minimal annual costs. Accessible to small-medium operations. Examples: satellite monitoring (<$500 setup, $10/hectare annual), generative AI subscriptions ($1,000-$3,000/year), basic IoT sensors ($2,500-$5,000).
- **Medium ($10K-$50K):** Initial investment $10,000-$50,000 with moderate annual costs. Suitable for medium-large operations or service models. Examples: AI disease detection systems ($5,000-$15,000 initial + $2,000-$5,000 annual), comprehensive IoT sensor networks ($10,000-$30,000), autonomous weeding service ($150-$300/hectare annual, no capital).
- **High (>$50K):** Initial investment over $50,000, often $150,000-$500,000+. Only viable for very large operations unless service models develop. Examples: robotic harvesters ($150,000-$500,000+), multi-task autonomous robots, comprehensive greenhouse automation systems.

1.3 Decision Framework

Based on the multi-criteria assessment, technologies receive one of three recommendations:

Adopt Now

- **Criteria:** High commercial readiness + Low-Medium adoption complexity + Low-Medium implementation cost
- **Characteristics:** Proven ROI (6-18 months), multiple vendors available, minimal technical risk, accessible to most growers
- **Action:** Prioritize for immediate investment. Use for capacity building and establishing data infrastructure foundation.

Pilot/Trial

- **Criteria:** Medium commercial readiness + Medium adoption complexity + Low-Medium implementation cost
- **Characteristics:** Strong academic validation, early commercial deployment, integration challenges remain, 2-3 year timeline to mainstream
- **Action:** Engage with demonstration programs (Gatton Smart Farm, ARC Research Hub trials). Support structured pilot projects with clear success metrics. Budget for 2-3 year adoption timeline.

Monitor

- **Criteria:** Low commercial readiness OR High adoption complexity OR High implementation cost
- **Characteristics:** Research/prototype stage, significant barriers to commercialization, 3-5+ year timeline, requires industry-wide coordination or major cost reduction
- **Action:** Track developments through research partnerships. Participate in government-funded research programs where appropriate. Focus current investment on proven technologies while maintaining awareness of future opportunities.

2. Master Technology Assessment

The following table presents a comprehensive assessment of 27 AI-enabled technologies for Australian vegetable production. Technologies are organized by decision category (Adopt Now, Pilot/Trial, Monitor) and scored across all four evaluation criteria. Complete details on each technology, including leading companies, evidence base, and implementation considerations, are provided in the Appendix.

Technology	AI Type	Commercial Readiness	Adoption Complexity	Implementation Cost	ROI Timeline	Decision
ADOPT NOW (9 Technologies)						
Soil moisture sensors & weather stations with AI analytics	Narrow AI	**High**	Low	Low ($2.5K-$10K)	12-18 mo	**Adopt Now**
Satellite crop monitoring with machine learning (NDVI analysis)	Narrow AI	**High**	Low	Low (<$10/ha)	12-18 mo	**Adopt Now**
Supply chain AI platforms (logistics optimization, demand prediction)	Narrow AI	**High**	Low	Low ($2K-$10K/yr)	6-12 mo	**Adopt Now**
Cloud-based irrigation optimization (AI scheduling & fertigation)	Narrow AI	**High**	Low	Low ($3K-$8K)	12-18 mo	**Adopt Now**
Generative AI for business support (minutes, compliance, inductions)	Generative AI	**High**	Low	Low ($1K-$3K/yr)	6-12 mo	**Adopt Now**
AI microclimate sensing & prediction platforms	Narrow AI	**High**	Medium	Medium ($10K-$25K)	12-18 mo	**Adopt Now**
LoRaWAN sensor networks with AI edge analytics	Narrow AI	**High**	Low	Low ($5K-$12K)	12-18 mo	**Adopt Now**
IoT post-harvest monitoring with AI prediction (ripeness, quality)	Narrow AI	**High**	Low	Medium ($15K-$30K)	12-18 mo	**Adopt Now**
Cold-chain tracking with AI anomaly detection	Narrow AI	**High**	Low	Medium ($10K-$20K)	12-18 mo	**Adopt Now**

Technology	AI Type	Commercial Readiness	Adoption Complexity	Implementation Cost	ROI Timeline	Decision
PILOT/TRIAL (11 Technologies)						
AI-powered crop disease detection (computer vision, 99% accuracy)	Narrow AI	Medium	Medium	Medium ($5K-$15K + $2K-$5K/yr)	24-36 mo	**Pilot/Trial**
Generative AI agronomist advisors (80% accuracy, requires verification)	Generative AI	Medium	Medium	Low ($1K-$3K/yr)	Variable	**Pilot/Trial**
Autonomous weeding robots (mechanical, service model)	Narrow AI	**High**	Medium	Medium ($150-$300/ha service)	18-24 mo	**Pilot/Trial**
Laser weeding systems (AI vision, 99% weed kill accuracy)	Narrow AI	Medium	Medium	High (service model developing)	18-24 mo	**Pilot/Trial**
Ultra-high-precision AI spraying (95% chemical reduction)	Narrow AI	Medium	Medium	High ($50K-$100K)	24-36 mo	**Pilot/Trial**
Automated pest monitoring traps with AI identification	Narrow AI	Medium	Low	Medium ($8K-$15K)	18-24 mo	**Pilot/Trial**
Vertical farming systems with AI climate control	Narrow AI	Medium	High	High (>$100K)	36-48 mo	**Pilot/Trial**
AI greenhouse automation (climate, irrigation, nutrients)	Narrow AI	Medium	High	High ($50K-$150K)	24-36 mo	**Pilot/Trial**
Vision-based automated grading & sorting in packhouses	Narrow AI	Medium	High	High ($100K-$300K)	36-48 mo	**Pilot/Trial**
AI seed variety selection (10m x 10m geographical precision)	Narrow AI	Medium	Low	Low (service model)	12-18 mo	**Pilot/Trial**
Autonomous drones with	Narrow AI	Medium	Medium	Medium ($15K-$35K)	18-24 mo	**Pilot/Trial**

Technology	AI Type	Commercial Readiness	Adoption Complexity	Implementation Cost	ROI Timeline	Decision
edge ML for crop monitoring						
MONITOR (7 Technologies)						
Automated harvesting robots (vegetable-specific)	Narrow AI	Low	High	High ($150K-$500K+)	36-60 mo	**Monitor**
Multi-task autonomous field robots	Agentic AI	Low	High	High ($200K-$600K+)	48-60 mo	**Monitor**
Fully autonomous farm systems (integrated multi-system AI)	Agentic AI	Low	High	High (>$500K)	60+ mo	**Monitor**
Fully autonomous agronomic AI (replacing human agronomists)	Agentic AI	Low	High	Medium ($10K-$30K)	60+ mo	**Monitor**
Digital twin farm simulation systems	Agentic AI	Low	High	High ($50K-$150K)	48-60 mo	**Monitor**
Blockchain traceability with AI analytics (industry standard)	Narrow AI	Low	High	Medium ($15K-$40K)	36-48 mo	**Monitor**
Integrated farm management AI (whole-farm decision automation)	Agentic AI	Low	High	High (>$100K)	60+ mo	**Monitor**

***Note:** Complete details on each technology, including leading companies, evidence base, case studies, and implementation considerations, are provided in Section 3 (Case Studies) and Appendix A (Company Directory).*

3. Case Studies: Implementation Pathways

The following case studies illustrate practical implementation pathways across the technology readiness spectrum. Each case study provides evidence-based analysis of real-world AI applications, demonstrating how the multi-criteria framework applies to specific technologies. The case studies span from proven commercial deployment (supply chain AI, OWL Project) through emerging trials (disease detection, generative AI advisors) to future potential (automated harvesting).

Case Study 1: Supply Chain AI Platforms

Decision: Adopt Now | AI Type: Narrow AI | Readiness: High | Complexity: Low | Cost: Low

Technology Overview

Supply chain AI platforms use narrow AI (machine learning, predictive analytics) to optimize logistics, predict demand, and provide real-time visibility from farm to retail. These platforms have matured over the past 5-7 years and represent the most commercially proven AI application for Australian vegetable growers.

Leading Example: AgriChain

AgriChain (Australia-wide) operates the most established agricultural supply chain AI platform in Australia with 15,000+ active users including traders, growers, bulk handlers, and carriers. The platform uses AI-powered logistics optimization and predictive analytics to provide end-to-end supply chain visibility with real-time tracking.

Demonstrated ROI

AgriChain users report:

35% reduction in marine insurance costs: AI risk assessment and real-time tracking reduce insurance premiums
65% reduction in credit cover costs: Transparent transaction history and automated documentation
6-12 month ROI: Through reduced paperwork, better market timing, and lower financing costs
50-70% reduction in manual paperwork: Automated contract generation, invoicing, and compliance reporting

AI-Enabled Integration

Supply chain platforms demonstrate ideal AI-enabled integration:

Augments existing processes: AI sits on top of current logistics operations, not replacing them entirely
Minimal infrastructure change: Cloud-based subscription model requires no capital investment
Low training requirements: Intuitive interfaces similar to consumer apps
Network effects: Value increases as more supply chain partners adopt the platform

Implementation Pathway

Phase 1 (Month 1-2): Platform setup, basic training, data migration

Phase 2 (Month 3-6): Integration with existing accounting/ERP systems, onboard key supply chain partners

Phase 3 (Month 7-12): Advanced features (predictive analytics, demand forecasting), full ROI realization

Adoption Barriers & Mitigation

Change management: Staff resistance to new systems. Mitigation: Demonstrate quick wins (time savings), provide hands-on training, champion-led adoption.

Supply chain partner coordination: Value maximized when partners also adopt. Mitigation: AgriChain's 15,000+ user base means partners likely already on platform.

Key Insight

Supply chain AI platforms represent the lowest-risk, highest-ROI AI adoption pathway for Australian vegetable growers. The technology is mature, proven, and requires no capital investment. The 'Adopt Now' rating reflects not just technical readiness but also change management simplicity - the primary barrier is organizational willingness rather than technical capability or cost.

Case Study 2: Open Weed Locator (OWL) Project

Decision: Pilot/Trial | AI Type: Narrow AI | Readiness: Medium | Complexity: Medium | Cost: Low-Medium

Technology Overview

The Open Weed Locator (OWL) Project, pioneered in Western Australia, demonstrates grower-led, open-source AI innovation. OWL uses low-cost computer vision (Raspberry Pi cameras) and machine learning to detect weeds in real-time, enabling precision spot-spraying that cuts herbicide use by up to 95%. Unlike expensive commercial systems ($50,000-$150,000+), OWL hardware costs ~$500-$2,000 using off-the-shelf components and open-source software.

Grower-Led Innovation Model

OWL emerged from WA growers frustrated with commercial technology costs. The project exemplifies the 'farmer hacker' movement:

Open-source design: Hardware plans, software code, and training datasets freely available
Grower-built: Farmers construct units using Raspberry Pi, cameras, and 3D-printed mounts
Collaborative development: International community contributes weed image datasets and algorithm improvements
Growing weed library: Expanding dataset improves accuracy across different crops and regions

Demonstrated Results

Early adopters in WA vegetable and grain operations report:

80-95% herbicide reduction: Spot-spraying only detected weeds vs. broadcast application
$10,000-$30,000 annual herbicide savings: Significant for large vegetable operations
6-18 month payback: Even with time investment for DIY construction
Environmental benefits: Reduced chemical use improves soil health and reduces resistance development

Why Pilot/Trial Rating Despite Proven Results?

OWL demonstrates technical and economic viability, yet receives 'Pilot/Trial' rather than 'Adopt Now' rating due to adoption complexity:

DIY technical skill required: Growers must build, calibrate, and troubleshoot hardware - not suitable for all operations
Crop-specific training needed: AI models must be trained on specific vegetables/weeds for optimal accuracy

Standardized evaluation lacking: Results vary by implementation - need consistent performance metrics
No service model yet: Unlike commercial alternatives, OWL requires grower technical capability

Pilot/Trial Investment Pathway

To advance OWL from pilot to mainstream adoption, structured support is needed:

Demonstration farms: Establish OWL units at Gatton Smart Farm and 2-3 regional sites for hands-on grower exposure
Vegetable-specific training datasets: Curate weed image libraries for key Australian vegetable crops (lettuce, brassicas, onions, carrots)
Standardized evaluation framework: Establish performance metrics (detection accuracy, herbicide reduction, reliability) for transferable results
Technical support network: Peer-led support (experienced OWL users mentoring new adopters) and online troubleshooting resources
Service model development: Support commercialization attempts (low-cost service providers building/maintaining units for growers)

Key Insight

OWL demonstrates that narrow AI for specific tasks (weed detection) can achieve strong ROI at low cost when delivered through open-source, grower-led models. The 'Pilot/Trial' rating reflects not technical limitations but the need for structured support to bridge from early adopters (technically sophisticated growers) to mainstream adoption. Investment in demonstration programs, standardized evaluation, and service model development could transition OWL to 'Adopt Now' status within 2-3 years.

Case Study 3: AI-Powered Disease Detection

Decision: Pilot/Trial | AI Type: Narrow AI | Readiness: Medium | Complexity: Medium | Cost: Medium

Technology Overview

AI disease detection uses computer vision and deep learning (Convolutional Neural Networks) to identify crop diseases, pests, and nutrient deficiencies from images. Academic research demonstrates 95-99% accuracy across multiple vegetable crops, with commercial systems like Fermata achieving 24/7 automated monitoring in controlled environments.

Academic Validation Foundation

Strong academic foundation supports commercial viability:

$5M ARC Research Hub (Griffith University): 5-year program developing machine vision AI for disease prevention and quality control
99.35% aggregate accuracy: Multiple Australian universities achieving high classification accuracy on vegetable diseases
54,306+ training images: Comprehensive datasets across 14 crop species, 26 diseases
Peer-reviewed validation: Frontiers in Plant Science (Feb 2024), Wiley/Plant Pathology (Sept 2024), Scientific Reports (May 2025)

Commercial Example: Fermata Croptimus

Fermata (International, serves Australia) provides the most mature commercial AI disease detection platform:

24/7 automated monitoring: Computer vision cameras scan crops continuously
30% crop loss reduction: Early disease detection enables targeted intervention
50% scouting time savings: AI replaces manual field inspections for initial detection

Controlled environment deployment: Currently proven in greenhouses, polytunnels where lighting/conditions controlled

Why Pilot/Trial Despite 99% Accuracy?

Despite strong technical performance, disease detection AI receives 'Pilot/Trial' rating due to integration challenges:

Farm management system integration: Connecting AI detection with existing software (spray scheduling, inventory management) remains challenging
Mobile field app development: Growers need practical field tools (smartphone apps with offline capability) rather than desktop systems
Open-field challenges: Variable lighting, weather conditions in open fields vs. controlled greenhouses reduce accuracy
Australian crop adaptation: Training datasets need Australian-specific vegetable crops, pests, diseases (not just global datasets)

Pilot/Trial Investment Pathway

Structured pilot programs can address integration challenges:

Phase 1 (Year 1): Controlled environment pilots - Deploy Fermata or similar systems in 5-10 Australian greenhouse vegetable operations (tomatoes, capsicums, cucumbers). Validate 30% crop loss reduction and 50% time savings claims in local conditions.
Phase 2 (Year 2): Open-field trials - Partner with ARC Research Hub (Griffith) to adapt systems for open-field vegetables (lettuce, brassicas, onions). Develop mobile field apps with offline capability.
Phase 3 (Year 3): Integration development - Build connectors to major farm management systems (Agworld, FarmIQ, etc.). Enable seamless workflow from AI detection alert to spray scheduling/treatment.

Success Metrics:

90%+ accuracy maintained in Australian open-field conditions
Seamless integration with at least 2 major farm management platforms
20+ growers achieving documented crop loss reduction
Mobile app with offline capability for remote areas

Economics

Medium-cost investment with strong ROI potential:

Initial investment: $5,000-$15,000 for camera systems, software licenses
Annual cost: $2,000-$5,000 for software subscriptions, system maintenance
ROI timeline: 24-36 months (faster for high-value greenhouse vegetables with disease pressure)
Suitable operations: Medium-large growers (20+ hectares or greenhouse operations) with disease/pest pressure

Key Insight

AI disease detection demonstrates the gap between research excellence (99% accuracy) and mainstream commercial viability (integration challenges). The 'Pilot/Trial' rating reflects not the AI's capability but the need for 2-3 years of integration development to create seamless workflows that fit existing farm operations. Early adopters with controlled environments (greenhouses) can benefit now, while open-field adoption requires structured pilot programs to validate and adapt systems to Australian conditions.

Case Study 4: Generative AI Agronomist Advisors

Decision: Pilot/Trial | AI Type: Generative AI | Readiness: Medium | Complexity: Medium | Cost: Low

Technology Overview

Generative AI agronomist advisors use large language models (LLMs) fine-tuned on agricultural data to provide crop management recommendations, answer grower questions, and assist with decision-making. Unlike narrow AI (which performs specific tasks like disease detection), generative AI creates new content - advisory text, recommendations, management plans - based on learned patterns from vast agricultural datasets.

Market Context

Generative AI in agriculture represents the fastest-growing AI segment:

Market growth: $216M (2024) projected to $2.0B (2034) at 25% CAGR (Precedence Research, May 2025)
Low barrier to entry: Subscription-based models ($1,000-$3,000/year) accessible to all farm sizes
Immediate deployment: No hardware required, works via web/mobile apps

Commercial Example: Agworld Alma

Agworld Alma (Australia) represents the most mature generative AI advisor currently deployed:

Currently deployed: Actively used by Australian vegetable and grain growers
80% accuracy: Human verification required for all recommendations
Pest management predictions: Climate forecasting, crop health insights
Continuous improvement: Machine learning from user interactions increases accuracy over time

Why Pilot/Trial Despite Current Deployment?

Agworld Alma is commercially available, yet receives 'Pilot/Trial' rating due to accuracy limitations and trust-building requirements:

80% accuracy insufficient: Cannot be used for autonomous decision-making - every recommendation requires agronomist verification
Australian data limitations: Training primarily on global datasets - needs more Australian-specific vegetable production scenarios
'Black box' concerns: Growers wary of how AI reaches recommendations - need transparent reasoning
Liability questions: Who is responsible if AI recommendation leads to crop loss?
Connectivity challenges: Cloud-based systems struggle in remote areas - edge deployment needed

Pilot/Trial Investment Pathway

Structured pilot programs can improve accuracy and build trust:

Phase 1: Vegetable-Specific Training (Months 1-6)

Partner with Agworld to train Alma specifically on Australian vegetable production scenarios
Curate training datasets: pest/disease management for lettuce, brassicas, onions, carrots, tomatoes, capsicums
Incorporate Australian-specific climate patterns, soil types, water availability scenarios
Target: Improve accuracy from 80% to 90%+ on vegetable-specific recommendations

Phase 2: Grower Pilot Program (Months 7-18)

Recruit 20-30 volunteer vegetable growers across regions (VIC, WA, QLD)
Pair each grower with agronomist advisor (human verification of AI recommendations)

Track accuracy improvement through systematic feedback loop
Measure trust evolution: grower confidence in AI recommendations over time
Target: Achieve 90%+ grower satisfaction, document 20-30% time savings on decision research

Phase 3: Transparency & Edge Deployment (Months 19-36)

Develop 'explain reasoning' feature - AI shows data sources and logic behind recommendations
Explore edge AI deployment for offline capability in remote areas
Establish clear liability frameworks (recommendations are advisory only, not instructions)
Target: Address 'black box' concerns, enable offline use, clarify legal/liability questions

Early Adoption Strategy

Even at 80% accuracy, generative AI advisors provide value when used appropriately:

Information gathering: Use AI to research options, compile information, suggest approaches
Hypothesis generation: AI proposes potential causes of crop issues, grower/agronomist validates
Time-saving on routine queries: AI handles common questions, freeing agronomist time for complex situations
Always verify with agronomist: Never implement AI recommendations without expert validation

Key Insight

Generative AI advisors demonstrate the potential and limitations of AI augmentation (not replacement) of human expertise. The 'Pilot/Trial' rating reflects the 3-5 year timeline to reach 95%+ accuracy required for confident adoption. However, low cost and immediate availability make generative AI ideal for confidence-building: growers can experiment with low risk, learn AI's capabilities and limitations, and establish data/workflow foundations for future higher-accuracy systems. This aligns perfectly with the staged adoption pathway - use simple generative AI now to build capability, advance to narrow AI production tools next, prepare for agentic AI future.

Case Study 5: Automated Harvesting Robots

Decision: Monitor | AI Type: Narrow AI | Readiness: Low | Complexity: High | Cost: High

Technology Overview

Automated harvesting robots use computer vision, robotic manipulation, and AI decision-making to identify ripe produce and harvest without human intervention. This represents one of the highest-complexity AI applications in agriculture, requiring integration of multiple technologies: vision systems (identify produce), AI assessment (determine ripeness), robotic precision (grasp without damage), and autonomous navigation (move through fields).

Technical Feasibility Demonstrated

Research proves technical feasibility, but commercialization remains challenging:

$4.1M Hort Innovation + Queensland DAF + GOFAR Program: 2024-2027 mechanization and robotics trials specifically for vegetable production
University research: University of Sydney and Queensland University of Technology demonstrated technical feasibility
International examples: RoboVeg (UK, broccoli), Muddy Machines (UK, asparagus), Four Growers (USA, tomatoes)
Challenge: Past commercialization attempts have failed despite research success

Why Monitor Despite $4.1M Investment?

Automated harvesting receives 'Monitor' rating due to multiple commercialization barriers:

1. Cost Prohibitive for Most Operations

Capital cost: $150,000-$500,000+ per unit
Annual maintenance: $20,000-$50,000 (specialized technicians, parts)
Viable only for: Very large operations (200+ hectares) or high-value greenhouse crops
Service models undeveloped: Robot-as-a-service (like SwarmFarm for weeding) not yet available for harvesting

2. Reliability & Gripper Technology Limitations

Damage rates: Current systems damage 10-20% of produce (vs. 2-5% for skilled human pickers)
Speed limitations: Robots slower than human crews, creating harvest timing challenges
Weather sensitivity: Vision systems struggle in rain, dust, variable lighting
Crop variability: Each vegetable requires custom gripper design and AI training

3. Infrastructure Requirements

Field modifications: Uniform plant spacing, clear pathways, standardized bed heights
Connectivity: Reliable internet for remote monitoring/troubleshooting (challenging in rural areas)
Technical expertise: Maintenance requires robotics/AI specialists (scarce in regional areas)
Organizational change: Shift from labor management to technology management

Current Research Investment Justification

Despite 'Monitor' rating, continued research investment is strategically important:

Labor challenges: Persistent seasonal labor shortages make automation increasingly critical
Technology trajectory: Costs declining ~15-20% annually as robotics/AI improve
International competition: Netherlands, USA advancing rapidly - Australia risks falling behind without sustained investment
Learning from failures: Past commercialization failures provide lessons for future attempts

Monitor Strategy: What to Track

Rather than investing in deployment now, industry should monitor these indicators:

1. Cost Reduction Trajectory

Watch for: Units dropping below $100,000 or service models emerging at $50-$100/hour
Timeline estimate: 3-5 years based on current technology cost curves

2. Reliability Improvements

Watch for: Damage rates dropping to <5%, harvest speed matching human crews
Key technologies: Soft robotics, advanced vision systems, weather-resilient designs

3. Service Model Development

Watch for: Companies offering harvest-as-a-service (similar to SwarmFarm weeding model)
Business model: Pay per tonne harvested, no capital investment required

4. GOFAR Program Results

Track: Outcomes from $4.1M Hort Innovation + Queensland DAF + GOFAR trials (2024-2027)
Key metrics: Demonstrated ROI, grower satisfaction, commercialization pathways

Appropriate Current Actions

For growers and industry bodies in the 'Monitor' phase:

DO: Participate in GOFAR demonstration days, track technology developments, maintain awareness
DO: Support continued research investment through levy funds (maintain Australia's capability)
DON'T: Make large capital investments in current-generation harvesting robots
DON'T: Expect immediate ROI - focus current investment on proven technologies (IoT, supply chain AI)

Key Insight

Automated harvesting illustrates the distinction between technical feasibility (research proven) and commercial viability (mainstream adoption). The 'Monitor' rating does not mean the technology is unimportant - rather, it signals a 3-5+ year timeline before cost, reliability, and service models align for widespread adoption. This represents appropriate risk management: support continued research (maintain capability), track developments actively (don't fall behind), but focus current capital on proven technologies (IoT sensors, supply chain AI) that deliver immediate ROI. When harvesting robots reach commercial viability, the data infrastructure established through today's 'Adopt Now' investments will enable seamless integration.

4. Conclusion: Strategic Implementation

This feasibility assessment validates the staged adoption pathway proposed in the VG24008 discussion paper through evidence-based analysis of 27 AI-enabled technologies. The multi-criteria framework provides clear guidance: 9 technologies ready for immediate adoption, 11 technologies suited for structured pilots over 2-3 years, and 7 technologies requiring continued monitoring over 3-5+ years.

Foundation: Capability Building (0-12 Months)

The 9 'Adopt Now' technologies - IoT sensors, satellite monitoring, supply chain AI, irrigation optimization, generative AI for business - share critical characteristics: proven ROI (6-18 months), low complexity, and accessibility to most growers. These technologies average $8,000 initial investment, creating accessible entry points that build confidence while establishing the data infrastructure foundation required for future AI applications.

Strategic insight: Low-cost generative AI for business management (compliance, inductions, reporting) provides the confidence-building experience necessary before advancing to higher-cost, higher-complexity production AI. The VG24008 consultation confirmed this pattern: growers show strong interest once exposed to simple demonstrations, highlighting the importance of building capability and trust incrementally.

Progression: Applied Pilots (1-3 Years)

The 11 'Pilot/Trial' technologies - AI disease detection (99% research accuracy), generative AI advisors (80% current accuracy), autonomous weeding robots, precision spraying - demonstrate strong technical capability but require structured pilot programs to address integration challenges. The case studies illustrate that the gap between research excellence and commercial viability is typically 2-3 years of focused integration development, not fundamental technical limitations.

Strategic insight: Early adopters with controlled environments (greenhouses) or high technical capability (OWL Project participants) can benefit from pilot technologies now, while mainstream adoption requires demonstration programs, standardized evaluation frameworks, and service model development. The $9.1M in active government programs ($5M ARC Research Hub, $4.1M Hort Innovation + GOFAR mechanization) provides the structured pathway from research to commercial deployment.

Preparation: Future Systems (3-5+ Years)

The 7 'Monitor' technologies - automated harvesting, multi-task robots, fully autonomous farms, agentic AI decision-making - remain in research/prototype stage with significant commercialization barriers. The automated harvesting case study demonstrates why 'Monitor' rating does not mean unimportant: technical feasibility is proven, but cost ($150,000-$500,000+), reliability (10-20% damage rates), and service model gaps prevent mainstream viability for 3-5+ years.

Strategic insight: Appropriate risk management means supporting continued research investment (maintain Australia's capability), tracking developments actively (don't fall behind international competition), but focusing current capital on proven technologies that deliver immediate ROI. When future systems reach commercial viability, the data infrastructure and organizational capability established through today's 'Adopt Now' investments will enable seamless integration.

Alignment with Industry Needs

This assessment aligns with international adoption patterns: AI progresses fastest in business management applications (compliance, quality assurance, administrative support) while production-level automation remains at pilot stage. The VG24008 consultation confirmed Australian growers follow this pattern, showing interest in simple, immediate applications (business support generative AI) before advancing to complex production systems (automated harvesting).

The staged pathway - capability building with simple tools (immediate), applied pilots for production support (2-3 years), system-level automation (3-5+ years) - respects this adoption trajectory while positioning the industry to capture benefits as technologies mature.

Critical Success Factors

Successful AI adoption requires:

Academic credibility over marketing hype: Lead with peer-reviewed research, demonstrated ROI, independent evaluation
Demonstration before investment: Gatton AgTech Showcase model - hands-on exposure builds confidence
AI-enabled integration: AI augments existing operations, not standalone replacement
Service models vs. capital expenditure: Subscription platforms and robot-as-a-service enable access
Data infrastructure foundation: IoT sensors provide data that all advanced AI requires

Final Assessment

The Australian vegetable industry has immediate access to proven AI technologies supported by world-class research and substantial government investment. Success depends on prioritizing evidence-based deployment (academic validation over vendor marketing), respecting adoption complexity (build capability before advancing to complex systems), and maintaining realistic timelines (6-18 months ROI for proven tech, 2-3 years for pilots, 3-5+ years for future systems).

The multi-criteria framework provides clear decision guidance: adopt proven technologies now (build foundation), pilot high-potential innovations (validate for local conditions), monitor future systems (track developments without premature investment). This staged approach maximizes ROI while positioning the industry for long-term competitive advantage as AI capabilities mature.

Assessment Prepared: October 2025

Primary Sources: Peer-reviewed academic publications, ARC Research Hub (Griffith University), CSIRO, Hort Innovation research programs, government investment analysis

Companies Assessed: 27 AI-enabled technologies, 20+ commercial companies with verified deployment

Consultation Base: VG24008 regional workshops (Victoria, Western Australia, Queensland), international technology research

Framework: Multi-criteria assessment (AI Type, Commercial Readiness, Adoption Complexity, Implementation Cost) with structured decision framework (Adopt Now, Pilot/Trial, Monitor)

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