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Enabling Responsible AI-Driven Agri-Food Innovation in Ontario: A Framework for Analysis of Adoption Challenges and Opportunities

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Abstract

AI adoption in the agri-food sector offers significant gains in productivity and competitiveness, but responsible implementation is essential to avoid stakeholder resistance and ethical concerns. This study examines the adoption of artificial intelligence (AI) technologies in Ontario's horticultural and livestock sectors. Applying a systems perspective and responsible innovation, it identifies and categorizes emerging AI applications, develops a conceptual framework to capture technological, social, environmental, individual, and institutional factors, and proposes practical strategies to promote adoption. A structured literature review of peer-reviewed articles, government reports, and industry publications was conducted to manually classify AI technologies into content layer classifications: descriptive, diagnostic, predictive, and prescriptive, and map them to a framework. Diagnostic and prescriptive technologies dominate in horticulture, while AI applications in livestock are fewer and more evenly distributed across functional layers. Out of the 24 technologies identified, only four technologies, three in horticulture and one in livestock, demonstrated all analytical functions, highlighting the need for more integrated AI solutions. Key barriers include high cost, interoperability challenges, data privacy concerns, technical skill gaps, and limited digital infrastructure. Recommendations include promotion of targeted institutional support, operational efficiency, and ethical data governance. The framework provides practical guidance for responsible AI adoption and a foundation for future empirical research.

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Keywords

structured literature review; AI adoption framework; AI ethics; inclusive innovation; interconnected systems; technology adoption; adoption barriers; SDG 9: Industry, Innovation, and Infrastructure

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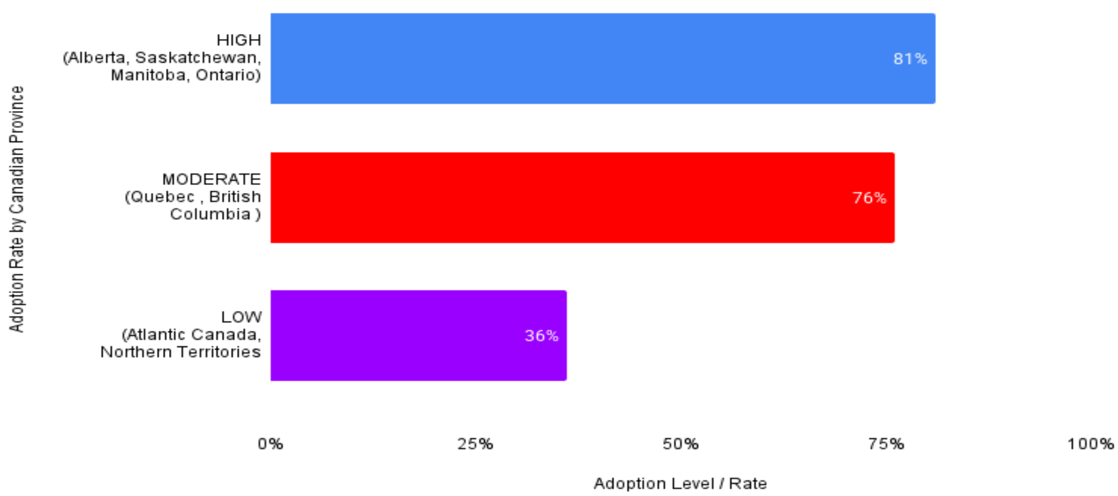
Introduction and Problem Statement

Innovations such as AI, robotics, and the Internet of Things (IoT) reshape farming practices and decision-making across the agri-food sector (Klerkx et al., 2019; Leader et al., 2020). Among these, AI plays a central role. It is defined as a computational construct that stimulates intelligence through algorithmic outputs, unlike human intelligence, which evolves biologically. AI is widely applied in agriculture to monitor crop and soil health, manage pests, and enhance yields through data-driven insights (Gignac & Szodorai, 2024).

In Canada, the total farmland area has remained relatively stable at around 158 million acres in 2016 (Statistics Canada, n.d.). Canada is also emerging as a leader in agricultural innovation, with the increasing use of precision tools such as crop monitoring software, drones, and machine learning (Greene & Murphy, 2021; Lemay & Boggs, 2024). Yet, adoption remains shaped by context-specific factors that are not always easily defined (Lemay et al., 2021).

Figure 1

Level of Technology Adoption in Canadian Agriculture



Note. Adapted from *"Barriers to Adoption: Digital Agriculture in Ontario's Food Production Landscape,"* by K. O. Twum, 2025 Canadian Agri-Food Policy Institute (CAPI). https://capi-icpa.ca/wp-content/uploads/2025/05/2025-05-23-Kwaku-Twum-Digital-Agriculture-EN.pdf

Figure 1 shows the technology adoption levels across Canadian provinces. Typically, large farms (>5000 acres) achieve high technology adoption, medium farms (2000–5000 acres) maintain moderate-to-high levels, and small farms (<2000 acres) continue to lag due to resource constraints (Lazurko et al., 2024; Lemay & Boggs, 2024; Twum, 2025).

Canadian provinces with higher technology adoption levels are better positioned to adopt advanced technologies, largely due to their large-scale operations, higher revenues, and institutional support, which favor investment in precision agriculture and digital tools (Twum, 2025). Sector-specific demands shape moderate level adoption, while structural challenges, such as farm sizes and limited infrastructure, drive low adoption (Twum, 2025).

Ontario, which accounts for over 25% of Canada's farms and 60% of its greenhouse area, plays a central role in the Canadian Agri-Food Sector (Hall et al., 2024; Rana et al., 2024; Hiebert et al., 2025). Farmers in the province use data-connected devices, remote sensing, robotics, and AI systems to enhance monitoring, prevent waste, automation, and decision-making (Hall et al., 2024; Smart Prosperity Institute., 2021). Dairy farming is a dominant sector, actively exploring AI and Big Data to address environmental challenges like methane emissions (Neethirajan, 2024; Rana et al., 2024). Beef cattle producers use technology mainly for breeding and herd management, while greenhouse farming is expected to be a future focus for innovation (Fonseka et al., 2024; Lazurko et al., 2024).

AI is gradually being integrated into Canadian agriculture, particularly in robotics, machine learning, and data analytics (Hall et al., 2024). In Ontario, its application is limited by high costs, poor broadband connectivity, interoperability challenges, weak stakeholder coordination, data privacy concerns, and pressure to increase sustainability without compromising productivity (Dara et al., 2022; Leader et al., 2020; Lemay et al., 2021; McCaig & Rezania et al., 2023 Neethirajan, 2024). Although these barriers are well-documented, they remain underexplored in Ontario's agri-food context, particularly in relation to how they can interact with AI technology functions to shape adoption decisions (Ahmed & Shakoor, 2025). This study addresses this gap by identifying emerging AI technologies according to their content-layer analytical functions. It shows how existing barriers can interact with these functions to influence adoption and outlines context-specific measures to support inclusive and responsible adoption in Ontario's agri-food sector. Ultimately, this understanding can encourage adoption, bridge knowledge gaps, and guide tailored institutional support that meets the specific needs of producers in Ontario's agri-food sector.

Conceptual Framework

The systems perspective highlights interconnected actors and interactions across technologies, processes, and institutions, and shows that effective systems depend on coordination, feedback loops, and adaptability (Arnold & Wade, 2015; Klerkx et al., 2012; Mansoor & Williams, 2024). Integrating AI into agriculture raises significant ethical and social concerns, including issues of privacy, animal welfare, and accountability (Dara et al., 2022; Papagiannidis et al., 2025). These concerns highlight the need for responsible innovation, emphasizing four key dimensions: including anticipation, inclusion, reflexivity, and responsiveness to ensure that technological advancements align with societal values and priorities (Gremmen et al., 2019; Massfeller, 2025). Similarly, responsible AI seeks to maximize benefits and minimize risks by aligning with eight key thematic trends: privacy, accountability, safety and security, transparency and explainability, fairness and non-discrimination, human control of technology, professional responsibility, and the promotion of human values (Papagiannidis et al., 2025). The systems perspective informs the identification of individual, social, and institutional factors shaping adoption patterns across horticulture and livestock sectors. Responsible innovation, in turn, guides the analysis of ethical, social, and governance issues, including privacy, accountability, and stakeholder inclusion. While the systems perspective highlights the need for robust infrastructure and institutional linkages, responsible innovation emphasizes stakeholder values, expectations, and governance concerns. Effective adoption, therefore, depends on coordinated systemic interventions (Klerkx et al., 2012). These perspectives structure the study's design and analysis, providing the foundation for the conceptual framework used to examine AI adoption in Ontario's agri-food sector.

Purpose

This review identifies and categorizes emerging AI technologies relevant to Ontario's horticultural and livestock sectors, develops a conceptual framework that captures the multidimensional factors influencing adoption, and proposes practical strategies for the responsible and inclusive integration of AI in agriculture. Ontario's horticultural and livestock sectors were selected due to their economic significance, diversity in production systems, and varying levels of digital readiness (Lemay & Boggs, 2024; Twum, 2025). Although over half of Ontario farms already use digital tools, adoption patterns vary across sectors and farm sizes (Hall et al., 2024). Combined with an aging producer base and growing calls for stronger public-private investment (Fonseka et al., 2024; Lazurko et al., 2024). Ontario emerges as an ideal setting to examine responsible AI adoption. More importantly, the province must leverage more than its natural advantages by strengthening innovation systems that integrate advanced technologies and promote global competitiveness (Lemay et al., 2021).

Methods

Using a structured literature review (Okoli, 2015), this study examined factors influencing technology adoption and AI applications in Ontario's horticulture and livestock sectors. The literature review was conducted between October and December 2024. Searches were conducted in Google Scholar using keyword combinations to identify relevant literature, including peer-reviewed journal articles, and grey literature from government agencies. Grey literature were further accessed directly through industry or academic institutional websites. Some peer-reviewed sources identified through Google Scholar may also be indexed in Scopus or Web of Science, but these databases were not directly prioritized due to limited institutional access and minimal added value. The limited volume of peer-reviewed studies on AI adoption in Canadian agriculture, particularly in Ontario, required consulting broader literature on digital agricultural technologies to identify adoption factors. Nevertheless, peer-reviewed sources were prioritized, with industry reports and technology provider websites used only to fill gaps and document practical AI applications. For instance, to identify AI technologies in Canadian agriculture, particularly in Ontario, we consulted technology developer websites such as SoundTalks, DeLaval, and Farmonaut.

Literature was identified using keywords such as “factors influencing AI adoption in Ontario livestock and horticulture,” “technology adoption,” “drivers and barriers of AI/digital technology adoption,” “digital/precision agriculture technologies,” “AI technology providers in agriculture,” “technology adoption in controlled environment agriculture,” “agri-food innovation systems,” “digital transformation in agriculture,” “Ontario agriculture,” and “Canadian agriculture.” Sources were primarily assessed for recency, with most published between 2022 and 2025 except earlier studies such as (Gremmen et al., 2019; Klerkx et al., 2012; Leeuwis & Aarts, 2011), which were included to provide a theoretical foundation. The included sources provided empirical or theoretical evidence on AI adoption and digital transformation, primarily focused on Ontario’s horticulture and livestock sectors. To contextualize findings, relevant studies from other Canadian regions or global settings were also considered when they offered relevant information. Studies were excluded if they were unrelated to AI adoption in agriculture or focused on non-Canadian contexts without broader applicability.

AI Technologies were documented and organized manually using Microsoft Excel, which served as the primary tool for organizing the literature. Data was organized across three Excel spreadsheets: the first recorded key study details (title, authors, publication date, aim, findings, source URL, and citation); the second categorized AI technologies by application e.g automated harvesting, animal identification, sector (horticulture or livestock), and function (e.g., disease detection, yield prediction), associated benefits, challenges, and the skills required for effective use were also identified. To avoid duplication, the review selected a single representative technology when multiple AI technologies addressed the same function. This process facilitated the further mapping of each technology to its corresponding analytical functions (Njuguna et al., 2025; Püschel et al., 2016). For example, Tools were categorized as descriptive (summarizing past patterns), diagnostic (identifying root causes), predictive (anticipating risks and outcomes), or prescriptive (recommending actions). No bibliometric or qualitative software was used; instead, manual synthesis was applied by sorting and comparing studies to identify recurring patterns. Findings were triangulated with industry and academic reports to enhance validity and guide the development of the conceptual framework. For the technology content layer, analysis relied on basic descriptive techniques such as frequency counts of functions, sectors, and applications, to identify patterns, which were summarized in a table. This approach aligns with scoping review guidance in Peters et al. (2020), where draft charting tables can be used to capture core study information and refined as the review progresses.

To develop the framework, we synthesized three key literatures on digital technology adoption in agriculture. Leeuwis and Aarts (2021) contributed a sociological perspective emphasizing trust, power dynamics, and policy influence across individual, social, and institutional levels. The ELSA framework (van Hilten et al., 2025), informed the normative and governance components of the study, aligning with principles of Responsible AI, including transparency, trust, regulation, data governance, and sustainability. Njuguna et al. (2025) further informed the individual level by highlighting cognitive factors, risk perception, alongside broader technological considerations such as technology performance and user capacity. Their work also outlined the analytical capabilities of digital technologies: descriptive, diagnostic, predictive, and prescriptive, which were integrated into the technological layer of the framework to understand the functions and practical applications of AI technologies in agriculture. The final framework was then adapted to align with the factors influencing adoption, while the technological content layer highlights how the characteristics of AI technologies interact with the interconnected levels.

While efforts were made to ensure objectivity, we acknowledge potential subjectivity in classifying AI technologies, especially when relying on commercial information that may overemphasize AI technology benefits over limitations. To mitigate bias, preference was given to peer-reviewed sources and government-backed reports, and information from industry websites, policy briefs, and reports was cross-checked against these sources. URLs to technology provider websites were documented for reference and verification, and inclusion/exclusion criteria were applied to filter sources lacking relevance or regional significance. Nevertheless, these considerations contextualize the study findings and encourage cautious interpretation. The following section presents the findings which are grounded in co-dependent systems perspectives, responsible AI, and content-layer classification of AI technologies (Leeuwis & Aarts, 2021; Njuguna et al., 2025; van Hilten et al., 2025).

Findings

The findings presented below reflect the study's objectives to identify and categorize emerging AI technologies relevant to Ontario's horticultural and livestock sectors; develop a conceptual framework that captures technological, social, environmental, individual, and institutional factors influencing adoption; and propose practical strategies for the responsible and inclusive integration of AI in agriculture.

Table 1

AI Technologies in the Horticultural and Livestock Sectors

AI Technology	Content Layer Classification				Sample Organization
	Descriptive	Diagnostic	Predictive	Prescriptive	
HORTICULTURE					
Plant Disease Prediction					Ukko Agro
AI Fertilizer application					Ukko Agro
AI Weeder					BH Frontier Solution
Climate Control systems for greenhouses					Hoogendoorn
Drone-based Real-Time Aerial Surveillance and Field Monitoring					Windwarddrones
Weed Prediction					GECO-Vancouver
Soil Health Monitoring					Chrysalab-Montreal
AI-driven Pollination Robotics					Arugga AI/Biobest Group
Produce Sorting using AI					Clrifruit AI
Automated/Smart Irrigation					Farmonaut
Automated Seeding & Harvesting					Haven Greens
AI-driven Farm Advisory Tool					Farmonaut
Quality Testing					P & P Optica
LIVESTOCK					
Animal Identification Based on Muzzle Prints					Onecup AI-Vancouver
Animal Identification Based on Biometrics					Onecup AI-Vancouver
Animal Identification Based on Retina Imaging					Onecup AI-Vancouver
AI Sensors for Respiratory Disease Detection in Swine					Soundtalks
Monitoring Livestock Health and Behavior					Herdwhistle-Alberta
Drone-based Livestock Management and Health Assessment					Zenadrone
Milk Yield Prediction					DeLaval
Automated Feeding Systems					DeLaval
Breeding Management					DeLaval
Sex Determination with integrated AI solutions					Hypereye-Montreal
Automated Calving Monitoring					Onecup AI-Vancouver

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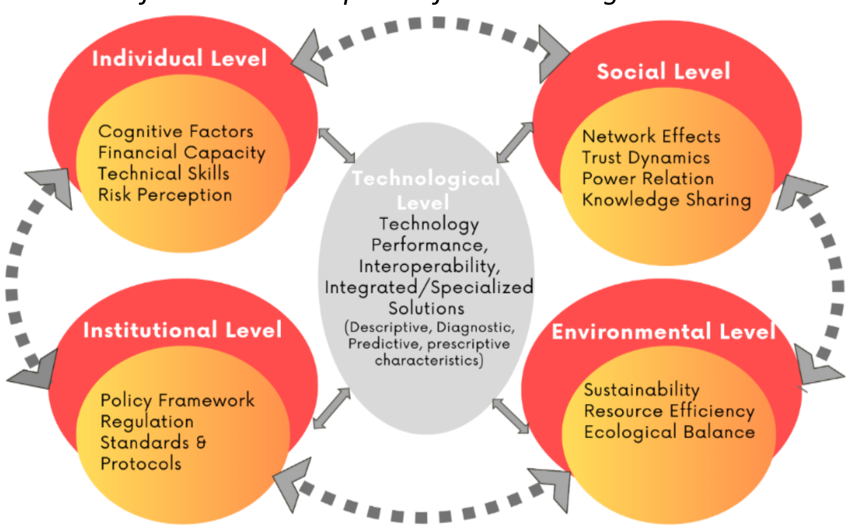
Table 1 presents twenty-four AI technologies, with a higher concentration of prescriptive and diagnostic technologies in horticulture, reflecting a trend toward tools that not only identify challenges but also offer solutions to optimize production. In contrast, livestock technologies show a more balanced distribution across the four content layer characteristics and are generally fewer in number compared to horticulture. Predictive tools are less common across both sectors, indicating opportunities for growth in AI technologies that can anticipate risks and future trends to inform decision-making. Generally, the distribution of AI tools across content layers reflects specific preferences, which may also hint at unique challenges and opportunities within sectors. A key observation is the potential for each layer to support the function of the next. Descriptive tools can gather raw data, diagnostic tools detect possible issues, predictive tools forecast risks, and prescriptive systems recommend actions. However, only four technologies were found to demonstrate all analytical functions, highlighting opportunities for further technology development in the sector.

This study develops a conceptual framework to examine how systemic factors across technological, social, environmental, individual, and institutional levels influence AI adoption.

Figure 2

Key Factors that Influence the Adoption of AI Technologies



Technological Level

Interoperability remains one of the greatest challenges in integrating digital technologies (Indira et al., 2023). It concerns the ability of diverse systems and devices to function together, with standardized data protocols, and is therefore significant in advancing digital adoption in Canada (Bioenterprise, 2024; Green et al., 2021; Lemay & Boggs, 2024). While there is clear potential for technological integration to enhance the operational efficiency of emerging tools (Lazurko et al., 2024), existing solutions are often specialized. For example, Huneke et al. (2024) found that Canadian Agri-tech organizations tend to be commodity-specific, with livestock, major crops, and vegetables each representing about one-quarter of those examined.

Furthermore, Phillips et al. (2019) observed that discussions on Canadian digital agriculture focus more on data governance, particularly ownership and control, than on the capabilities of the technologies. These debates are especially relevant due to the central role of big data in advancing sustainability and optimizing agricultural operations (Birch & Bronson, 2022; Bronson, 2022; Dara et al., 2022; Neethirajan, 2024). However, examining digital tools through the technology content layer offers a complementary perspective by clarifying how AI technologies can inform policy and create value through their analytical functions. Classifying these tools within a structured taxonomy enables a clearer understanding of their role in supporting decision-making (Püschel et al., 2016).

Social Level

Factors such as power relations, network effects etc play a key role in technology adoption. For instance, information sources from peers, extension services, media, or training shape individual perception of the technology, and can determine how it is viewed as useful, trustworthy, or risky (Leeuwis & Aarts, 2021). Similarly, Canadian farmers are more likely to adopt technologies when they observe others in their networks doing so (Bioenterprise, 2024; Hall et al., 2024). Although digital technologies can improve efficiency and yields, they also create new challenges such as skill divides, rising land costs, and questions over control of digital data. These carry social implications, including potential risks of exploitation for marginalized groups (Leader et al., 2020; Makinde et al., 2022). Power dynamics further influence who benefits, with adoption often favoring larger, more educated, or multi-generational farms (Wang et al., 2016).

Environmental Level

Environmental factors influence technology adoption by encouraging solutions that reduce waste, support ecological balance, and meet environmental standards (van Hilten et al., 2025). AI plays a dual role in agriculture, simultaneously helping to mitigate environmental pressures while contributing to them. AI tools optimize resource use and reduce methane emissions, supporting sustainability goals in high-value sectors like Ontario's dairy industry (Hall et al., 2024; Neethirajan, 2024). On the other hand, AI's high energy demands raise environmental concerns, emphasizing the need for low-energy solutions tailored to agricultural contexts (Raghav et al., 2024).

Individual Level

Adoption is often understood at the individual level as a process where decisions rely on personal evaluation and judgment (Leeuwis & Aarts, 2021). Farmers may adopt technologies to increase yields, reduce labor, or pursue sustainability (MacPherson et al., 2022). Nevertheless, the extent of adoption depends on whether these tools align with their knowledge, skills, and existing practices (Chowdhury et al., 2025). Evidence from Canadian farmers shows varying perceptions as technology adoption in Canadian agriculture depends less on availability but on farmers' unique needs and contextual factors (Lemay et al., 2021). While some view digital tools as supportive, others see it as unreliable (McCaig & Dara et al., 2023). This suggests that adoption can be relational, shaped by confidence in providers and institutions (Hall et al., 2024). Trust in providers and institutions, therefore, becomes critical, as credibility encourages experimentation and reduces uncertainty (Hall et al., 2024). At the individual level, the aging demographic of Ontario farmers raises succession concerns, shaping risk preferences and openness to innovation (Hall et al., 2024). Financial capacity further influences adoption, favoring those better positioned to absorb high upfront costs (Green et al., 2021).

Institutional Level

AI adoption can leverage on existing foundations of local Canadian innovation capacity supported by research initiatives, precision agriculture start-ups, and big data platforms. Yet, weak connections to global networks limit broader diffusion and scalability (Phillips et al., 2019). Adoption remains highly context dependent. Lemay and Boggs (2024) observe that uptake is shaped by farm type, infrastructure availability, and the policy environment. Even where technologies show clear benefits, their impacts depend on inclusive, region-specific policies that align innovation with ecological and social priorities (Green et al., 2021). Infrastructure gaps worsen these challenges. Limited rural broadband access continues to constrain adoption in Ontario, forcing some farms to rely on costly alternatives such as Starlink (Greig et al., 2023; Hall et al., 2024). Without reliable connectivity, digital tools remain out of reach for many producers, slowing diffusion and reinforcing existing divides. Ethical and governance issues shape farmer's decisions as poorly designed AI systems risk undermining trust, raising animal welfare concerns, and compromising privacy (Greig et al., 2023; Hall et al., 2024). At the same time, the concentration of power in multinational agribusiness firms exacerbates fears around data rights and reinforces structural inequities (Dara et al., 2022)

Table 2 links technology content layer classifications to the framework in Figure 2 above, reflecting how interrelated factors may further influence AI adoption.

Table 2

Relating Technology Content Layer Classification with Other Factors Influencing AI Adoption

Content Layer Classification of AI Tech.	Analytical Function	Examples	Possible Adoption Barriers	Factors Likely to Influence Adoption	Potential Drivers
Descriptive	*What is happening?*	Soil health Monitoring	Data variability, lengthy data processing time, interoperability issues	Individual, Institutional	Standardized data formats, reliable infrastructure, and technical assistance
Diagnostic	*What problems exist?*	AI Sensors for respiratory disease detection	May require technical expertise, data privacy concerns	Individual, Social, Institutional	Availability of Skilled labor, Advisory support, and Knowledge sharing opportunities
Predictive	*What might happen?*	Milk yield prediction	High costs, risk of environmental damage due to unreliable data	Individual, Social, Environmental, Institutional	Demonstrated benefits, financial incentives, and training support
Prescriptive	*What can be done?*	Automated irrigation systems	High upfront costs, lack of trust in recommendations	Individual, Institutional	Appropriate regulatory framework, transparent data practices, policy incentives

Table 2 highlights how social, institutional, and environmental contexts interact with AI technology functions to influence adoption, while Figure 3 illustrates the links between these systemic factors and corresponding analytical functions.

Figure 3

Interaction of Technological Content Layers with Other Systemic Factors Influencing AI Adoption

The conceptualization of technological functions across systemic factors shows adoption as a continuous, interactive process rather than a linear one, enabling engagement across multiple levels. The inherent complexity of AI systems present adoption challenges that require proactive strategies to prevent harmful societal impacts (Buhmann & Fieseler, 2021; Raman et al., 2024). Key concerns such as unemployment, privacy, bias, misinformation, and digital inequities, give rise to the need for equitable, inclusive data-sharing agreements aligned with societal interests (Birch & Bronson, 2022; Polyportis & Pahos, 2024; Twum, 2025). Technical solutions like standardized APIs, open-source platforms, and integrated systems can support data optimization (Lemay & Boggs, 2024). Preparing farmers, agricultural workers, and rural communities for digital transitions also demands proactive state involvement and a multi-stakeholder approach centered on early engagement, participatory co-design, and ongoing reflection on ethical, social, and cultural implications (Buhmann & Fieseler, 2021; Leader et al., 2020; Polyportis & Pahos, 2024).

Conclusions, Discussion, and Recommendations

This review examined emerging AI technologies in Ontario's horticultural and livestock sectors and the key factors shaping their adoption. Using the technology content layer classification, it analyzed how AI functions support agricultural decision-making, then developed a framework linking these layers with systemic factors to broaden understanding of adoption. Horticulture favors diagnostic and prescriptive tools that not only identify issues but also optimize production, while livestock technologies are fewer and more evenly distributed across all four content layers. Yet only a few technologies demonstrated all analytical functions, Focusing on the content layer classification offers a structured view of technology functions, but could overlook the broader contextual factors influencing adoption as observed by (Outcault et al., 2022). According to Ndah (2015), adoption is shaped by both technological and non-technological factors, Leeuwis and Aarts (2021) also emphasize that adoption rarely occurs in isolation but within interrelated system dynamics. Responsible innovation further reinforces this perspective, emphasizing that effective solutions must emerge through stakeholder engagement and practical action (Kroesen et al., 2015). This justifies the value of a framework that links technological content layers with systemic factors to capture the complexity of AI adoption in Ontario's agriculture.

The theoretical perspectives applied in this study informed both the design of the framework and the interpretation of findings. The AI technologies identified in this study are often specialized in one to three content layer functions, with few possessing all content layer analytical capabilities. Tailored AI applications improve resource management by enabling timely interventions (Miller et al., 2025). However, interoperability adds value by linking data within farms and across the value chain (Lemay & Boggs, 2024), yet it requires integrating diverse data formats, naming conventions, and operational requirements into a unified framework, which may pose significant technical challenges (Ahmed & Shakoor, 2025; Lemay & Boggs, 2024). Furthermore, the interaction of the functional capabilities of AI with systemic factors, reveal the broader conditions under which adoption occurs. For example, descriptive analytics depends on standardized data and reliable infrastructure, yet barriers such as weak interoperability, limited broadband, and fragmented institutional support often constrain implementation. At the same time, adoption requires synchronised investment in farmer upskilling and policy support to build familiarity with AI tools. Trust in providers reinforced by networks of positive influence further reduces uncertainty and encourages use. These dynamics reflect a systems perspective, where innovation emerges from managing interdependencies across technology, society, economy, and institutions (Arnold & Wade, 2015; Klerkx et al., 2012; Mansoor & Williams, 2024).

The framework proposed in this study can be applied in qualitative data collection through interviews with key informants as well as quantitative surveys to assess stakeholder perspectives. It can also be used as a case study tool to examine specific AI technologies, allowing for further refinement. The next step in this research will empirically test the framework to identify the most critical factors for targeted interventions in Ontario. A SWOT analysis guides the identification of internal (strengths, weaknesses) and external (opportunities, threats) factors (Puyt et al., 2023). These factors will then be evaluated using the Analytic Hierarchy Process (AHP), which uses pairwise comparisons in decision making, allowing for a deeper understanding of these findings and a transparent prioritization of key AI adoption drivers to inform targeted strategies, and policies (Ishizaka & Labib, 2011; Saaty, 1987). Future research could examine stakeholder priorities to contextualize these findings across agri-food sectors and uncover sector specific adoption drivers.

Although the focus of this study was Ontario, AI technologies from firms in other provinces were often used as proxies where Ontario-specific data was unavailable. While this introduces a minor limitation, it does not detract from the overall objective of mapping key AI technologies in agriculture. Overall, the findings highlight that the successful adoption of AI in agriculture depends not only on technological advancements but also on reducing systemic barriers while cultivating trust among stakeholders, addressing ethical concerns, and establishing robust regulatory frameworks.

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