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Digital transformation in Canadian crop production: A scoping review of technologies, adoption drivers, and systemic barriers

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A B S T R A C T

Digital agricultural technologies are widely promoted as pathways to improve productivity, profitability, and environmental performance in crop production. Yet their development, validation, and adoption vary significantly across contexts. This scoping review synthesizes evidence from 64 Canadian and international studies published since 2013 to (i) identify DATs developed, piloted, or validated in major Canadian field crops, and (ii) examine stakeholder perspectives on their adoption. Following PRISMA-ScR guidelines, we reviewed peer-reviewed and grey literature on soil sensing, thematic soil mapping, soil moisture estimation, crop and yield prediction, fertilization optimization, pest and weed detection, and precision planting. Most technical studies focused on sensing-based and analytics-driven applications, often using machine learning with proximal or remote sensing data. These technologies demonstrated strong predictive performance under localized conditions, particularly for soil properties, soil moisture, and yield estimation, but frequently lacked cross-regional calibration, long-term validation, and integration into decision-support systems. The evidence base is dominated by studies on oilseed and grain systems, reflecting Prairie and Ontario field crop production, with comparatively limited attention to specialty crops and robotics-intensive operations. Adoption studies identified cost–benefit considerations, data governance and privacy concerns, interoperability challenges, and uneven advisory capacity as key determinants of uptake.

Interpreting the evidence through a sectoral innovation systems lens reveals structural constraints shaping Canada’s digital agriculture trajectory, including concentrated public funding, limited commercialization pathways, regional imbalances in testing environments, and underdeveloped data governance frameworks. These findings underscore the need for a Responsible Research and Innovation approach for coordinated and regionally distributed validation, stronger advisory and training systems, clearer data governance, and responsible innovation practices. The review provides an integrated evidence base to inform policy and investment strategies that support an equitable and effective digital transformation of Canadian crop production.

1. Introduction

Meeting the food demands of a global population projected to reach 9.7 billion by 2050 requires agricultural systems that are both more productive and more sustainable [1,2]. These pressures are particularly acute for major exporting countries. Canada is among the world’s largest agri-food exporters, with exports exceeding CAD 100 billion annually and a high share of crop production destined for international markets [3]. Yet, agricultural total factor productivity has stagnated since around 2010, and the sector remains responsible for roughly 10 % of national greenhouse gas emissions, alongside ongoing concerns about soil degradation and water contamination [4,5]. Reconciling productivity, profitability, and environmental goals has therefore become a central policy and research challenge.

Digital agriculture is framed as a technology enabled, data driven approach to improve efficiency by managing fields, crops and livestock, and observing, measuring and acting on site specific conditions using information and communication technologies and analytics. Digital agricultural technologies (DATs), including remote sensing, Internet-of-Things (IoT) devices, robotics, artificial intelligence (AI), and data analytics, are widely promoted as a cornerstone of digital agriculture, “Agriculture 4.0″ and smart farming. The field is often described as a “sense-process-act” paradigm in which sensing and data collection feed processing and decision systems that in turn generate actions on the farm. Table 1 summarizes the principal components and how each contributes to the overall digital agriculture workflow in practical terms.

Global reviews have mapped how digitalization is reshaping agricultural production, value chains, and food systems. For example, Abbasi et al. [13] provide a systematic literature review of Agriculture 4.0, cataloguing the range of digital technologies and highlighting emerging trends in automation, connectivity, and AI. Together, these studies underline the transformative potential of DATs but remain

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Table 1
The operational workflow in digital agriculture.

Component	Purpose	Example technologies	Typical mechanism
Sensing	Acquire field and animal state	Soil probes, UAVs, satellites, cameras	Convert physical measurements into digital, georeferenced streams for fusion [6,7].
Connectivity	Move data to processors	WSN, LPWAN, 4G/5 G, gateways, fog/edge	Local aggregation and preprocessing at edge; send prioritized data to cloud [8,9].
Processing and storage	Hold and prepare data	Cloud platforms, databases, bigdata stacks	Ingest, clean, fuse heterogeneous data; provide scalable retrieval [10,11].
Analytics and decision support	Produce actionable outputs	ML models, statistical algorithms, rule engines	Predict yield/disease, generate prescriptions and alerts [6,10].
Actuation and automation	Implement decisions	VRT applicators, irrigation controllers, robots	Translate prescriptions into control signals and autonomous tasks [7,12]

largely global and conceptual, with limited attention to how specific technologies perform in particular agroecological and policy contexts. The other set of studies identify recurring technical and sociotechnical barriers that influence how technologies are implemented. For example, Klerkx et al. [14] synthesize emerging social science work on digital agriculture and identify thematic clusters related to adoption, labour, power and data governance, knowledge and innovation systems, and the economics and management of digitalized production. They further emphasize the need for research on digital policy processes and the geography of digital agriculture.

Recently, more geographically focused work has begun to examine how digitalization is unfolding in Canada. Green et al. [15] conducted a scoping review of the “digital agricultural revolution” and ecosystem services, emphasizing that while DATs are frequently justified in terms of environmental benefits, empirical evidence on ecosystem-service outcomes remains thin and uneven, and calling for more context-specific research to inform Canadian policy. Ebrahimi et al. [16] developed a framework for systematic stakeholder inclusion in digital agriculture, using Canada as a test case to map the diverse actors in the digital agriculture ecosystem and to situate this within the Responsible Research and Innovation (RRI) agenda. Complementing these analyses, Glaros et al. [17] examined digital technologies in local agri-food systems, focusing on agriculture e-commerce in Ontario and identifying interoperability and platform fragmentation as key challenges in the “digital farmgate” sector.

At the same time, new empirical work has emerged on Canada’s agri-tech industry. A recent national analysis of Crunchbase data identified 247 Canadian agricultural technology organizations developing digital tools for agriculture, most of them small to medium-sized enterprises located in metropolitan regions and focused on in-field applications and software- or platform-based solutions [18]. These organizations commonly emphasize business benefits such as labour savings, enhanced decision-making, and increased output, while environmental and social benefits are communicated less consistently and vary across regions. This work provides a valuable picture of the firms producing digital technologies but does not examine how specific DATs perform in crop production systems, nor how producers and advisors perceive and adopt them.

Taken together, these contributions show that Canada is often portrayed as an early mover and “leading country” in digital agriculture, with substantial public investment in AI and data-driven innovation [16]. However, three important gaps remain. First, existing Canadian-focused syntheses either take a broad ecosystem or stakeholder lens (e.g., stakeholder mapping, ecosystem services, firm-level analysis) or focus on specific segments of the value chain, such as local food e-commerce, rather than on DATs deployed in primary crop production. Second, we lack a consolidated picture of which digital technologies have been developed, piloted, or validated in major Canadian field crops, what data and modelling approaches they use, and how they perform in agronomic and, where available, economic terms. Third, although social science reviews document adoption barriers and tensions around data governance at a general level [17,14], there is limited synthesis of empirical studies that examine how Canadian producers, advisors, and other stakeholders perceive DATs in practice, and how these perceptions intersect with funding patterns, regional disparities, and innovation-system dynamics.

Focusing on Canada helps address these gaps for at least two reasons. First, Canada’s combination of export-oriented, industrialized agriculture; large spatial gradients in climate and agroecology; and a strong, publicly supported research system makes it a revealing case for understanding how DATs move from experimentation to uptake. Second, Canada’s experience is relevant internationally for other high-income, export-oriented countries (e.g., Australia, the United States, parts of Europe) that face similar pressures to increase productivity while meeting ambitious climate and biodiversity targets and navigating questions of data governance, rural equity, and responsible innovation [19–21]. Insights from a country-level synthesis of DAT development and adoption in Canadian crop systems can therefore inform wider debates about how to design policy and funding instruments that align digital innovation with both producer decision-making and broader sustainability objectives.

This study adopts a scoping review approach to systematically map the breadth, characteristics, and maturity of DATs applied to Canadian crop production. A scoping review is particularly appropriate given the diversity of technologies, data sources, analytical methods, and outcome measures reported across the literature. Rather than evaluating intervention effectiveness, the review aims to identify dominant research trends, evidence gaps, and structural constraints shaping DAT development and adoption in Canada. The findings are intended to inform three audiences: policymakers seeking to align innovation and sustainability objectives; practitioners and producers evaluating the readiness of DATs for on-farm decision-making; and researchers identifying priorities for future empirical and methodological work. This scoping review responds to these gaps by systematically mapping DATs applied to major Canadian field crops and synthesizing evidence on stakeholder perspectives regarding their adoption. Specifically, we: (i) catalogue DATs that have been developed, piloted, or empirically evaluated in major Canadian crop production since 2013, including their intended uses, data sources, and analytical approaches; (ii) summarize reported agronomic and, where available, economic outcomes; and (iii) synthesize stakeholder perspectives on the drivers and barriers to adoption of DATs in Canadian crop systems. We interpret these findings using a sectoral innovation systems (SIS) lens, linking patterns in DAT development and adoption to funding sources, regional distributions, and broader governance debates around responsible digital agriculture. By doing so, the review offers a country-level evidence base that complements global reviews of digitalization and social-science analyses of digital agriculture, while providing policy-relevant insights for Canada and other jurisdictions navigating the digital transformation of agriculture.

2. Methods

This scoping review followed the PRISMA-ScR framework [22,23] and adhered to a protocol developed in advance according to PRISMA-P guidelines [24]. The protocol was registered and published in the University of Calgary’s Digital Repository [25].

2.1. Eligibility criteria

Eligibility criteria were defined using the Population–Intervention–Comparator–Outcome–Study Design (PICOS) structure as outlined in the protocol [26]. The population of interest was major Canadian field crops during the growing season [27]. Eligible interventions included DATs used by producers or advisors to support decision-making. DATs were defined as technologies involving:

1. data collection (e.g., proximal or remote sensors),
2. data integration and analysis (e.g., machine learning or statistical modelling), and
3. generation of decision-support outputs (e.g., maps, dashboards, or screens).

Studies were included if at least one of these steps involved a commercially available technology in Canada and if the evaluation was conducted within Canada. Eligible studies were required to include a concurrent comparison (e.g., alternative practice, technology, or analytical method) and examine applications such as soil and crop property prediction, yield estimation, soil moisture mapping, fertilizer optimization, pest or weed detection, irrigation scheduling, or precision planting.

For technology-assessment studies, extracted data included crop type, intended use, data-gathering methods, analytical approaches, statistical models, and performance outcomes. For perception-based studies, extracted elements included stakeholder characteristics, recruitment strategies, theoretical frameworks, analytical methods, and findings related to motivators and barriers to DAT adoption. Only English-language sources with full text available in peer-reviewed journals, theses, or conference proceedings were eligible.

2.2. Information sources and search strategy

A comprehensive search was conducted on November 27, 2023, in five electronic databases: CAB Abstracts, BIOSIS, Web of Science, IEEE Xplore, and ProQuest Dissertations. A research librarian developed the search strategy using controlled vocabulary and keywords related to digital agriculture technologies. Searches were limited to English-language publications from 2013 onward. Full database search strings are provided as Supplementary Material. Search results were imported into Covidence (Veritas Health Innovation, Melbourne, Australia) for screening and deduplication. An earlier scoping review [15] was cross-checked to ensure adequate retrieval of relevant studies. Additional records were identified through reference checking and manual searching [28,29].

2.3. Selection of sources of evidence

Study selection was conducted in two stages by two independent reviewers. Prior to each stage, reviewers calibrated their interpretation of the inclusion and exclusion criteria (see supplementary material). In Stage 1, titles and abstracts were screened using signaling questions from the protocol. In Stage 2, full texts were assessed for eligibility, with reasons recorded for all exclusions. Conflicts were resolved through discussion; a third reviewer adjudicated unresolved disagreements [30].

2.4. Data synthesis and analytical framework

Data synthesis followed an iterative and descriptive approach consistent with PRISMA-ScR guidance. Included studies were first categorized by digital agricultural technology application, including soil property prediction, thematic soil mapping, soil moisture estimation, crop and yield prediction, fertilization optimization, pest and weed management, precision planting, and irrigation. Within each category, studies were further grouped by data source (e.g., proximal sensing, remote sensing, satellite, UAV, in-field sensors), analytical approach (e.g., statistical modelling, machine learning, simulation models), spatial and temporal scale, and reported outcomes. In addition to technical performance metrics, we extracted information on validation scope, decision-support integration, economic assessment, and stakeholder engagement where available. This structured synthesis enabled comparison across application domains while preserving contextual detail relevant to Canadian agroecological and institutional conditions. Two independent reviewers extracted data into structured Microsoft Excel tables. Extracted information included study identifiers, funding sources, study location, crops evaluated, intended use of the technology, data collection methods, analytical techniques, and statistical outcomes. For perception studies, data items also included stakeholder group, theoretical or analytical framework, recruitment strategies, and contextual information about technology use. Extraction templates were piloted and refined to ensure consistency.

To interpret the synthesized findings, we used a SIS framework, which examines interactions among entrepreneurs, producers, scientists, technology firms, and policymakers engaged in the development, commercialization, and adoption of DATs [31–33]. The SIS lens supports an integrated understanding of how technological, institutional, and market factors influence digital innovation trajectories in Canadian agriculture. The framework is described in Fig. 1.

2.5. Synthesis of results and study limitations

A narrative synthesis approach was applied. For studies evaluating DATs, results were organized by intended application (e.g., soil property prediction, yield estimation). Summary tables reported the number of studies by crop, data-collection method, analytical model, and statistical performance. Where more than two studies were available within a category, comparative matrices were constructed to identify patterns across crops, data sources, and analytical approaches [15].

For studies on stakeholder perceptions, findings were grouped by stakeholder type. Determinants of DAT adoption were classified into individual, relational, and broader contextual factors.

Consistent with scoping review methodology, formal quality scoring or risk-of-bias assessment was not conducted. However, several limitations and potential sources of bias were systematically documented. First, the literature is dominated by technical performance studies conducted under controlled or localized conditions, which may overrepresent predictive accuracy relative to real-world applicability. Second, publication bias toward positive results is likely, particularly for machine learning–based studies. Third, the review was limited to English-language sources, introducing potential language bias. Finally, the reviewed literature is heavily concentrated on major field crops, particularly oilseeds and grains, which dominate production in the Prairie provinces of Alberta, Saskatchewan, and Manitoba. These systems typically emphasize large-scale, mechanized operations where digital technologies focus on soil sensing, yield prediction, nutrient management, and broad-acre input optimization. In contrast, fruit and orchard systems in British Columbia, which require precision spraying, canopy sensing, and robotic harvesting solutions, are sparsely represented in the reviewed studies. Similarly, corn and soybean systems in Ontario, which support higher adoption of variable-rate technologies and decision-support tools, are more frequently studied than potato and vegetable systems in Atlantic Canada, where field-scale automation and robotics face different operational constraints. As a result, the evidence base captured in this review is weighted toward digital technologies developed and tested for broad acre cropping systems. These limitations are considered explicitly in the Discussion and inform interpretation of the evidence base.

3. Results

A total of 64 studies met the inclusion criteria (Fig. 2). Of these, 57

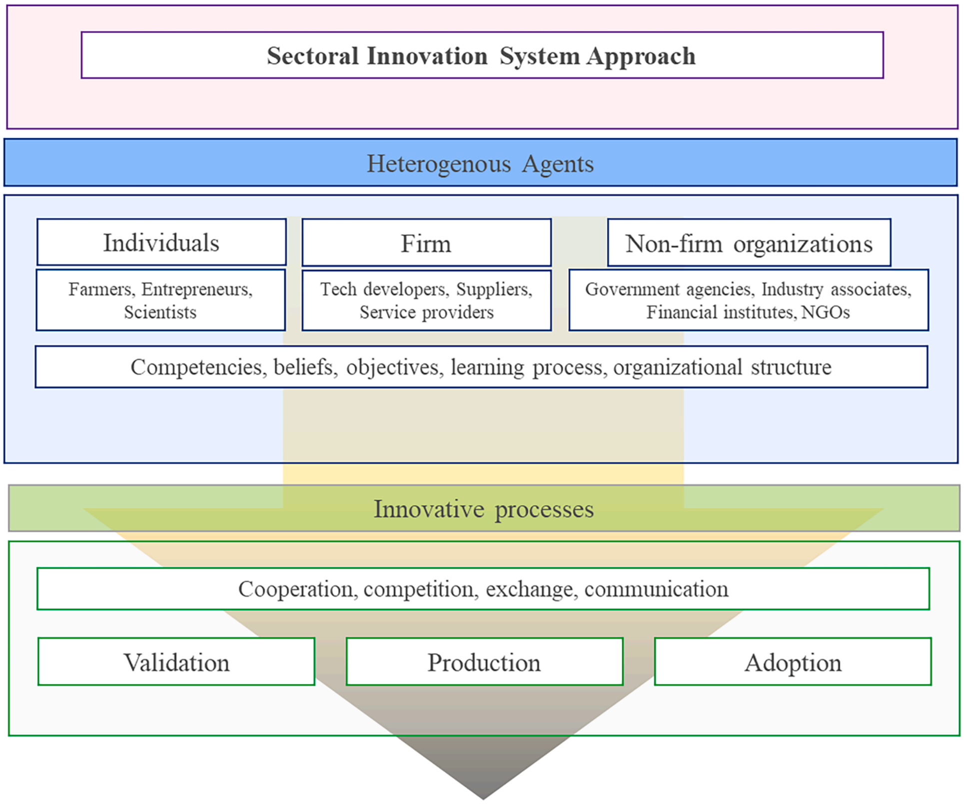

Fig. 1. Sectoral Innovation System approach framework in a scoping review of agricultural digital technologies developed and assessed in main crops and barriers and motivators of different stakeholders for their adoption in Canada.

evaluated DATs in Canadian crop systems, while seven examined stakeholder perceptions regarding adoption.

The studies were categorized based on the application of DATs in various stages of crop production. A majority of studies targeted applications related to soil property estimation and crop yield prediction Fig. 3.

These technologies were most frequently tested in Ontario, followed by Manitoba. Fig. 4 presents a detailed breakdown of the selected studies by province.

3.1. Digital technologies used in major Canadian crops

3.1.1. Soil properties prediction

Estimating physical, chemical, and biological soil attributes, such as texture, organic matter, nutrient content, pH, soil electrical conductivity, and cation exchange capacity, is essential for effective zone delineation and management. Traditionally, soil assessment has relied on labour-intensive surveys and lab analyses. However, advancements in sensor technology have enabled the mapping of soil heterogeneity more efficiently. This review identified fourteen studies focused on DATs for estimating physical, chemical, or biological soil attributes [34–47]. Twelve used proximal soil sensing (PSS) techniques such as electromagnetic induction (EMI), mid-infrared spectroscopy, gamma-ray detection, or smartphone imagery. These methods reduced reliance on labour-intensive soil sampling and enabled high-density spatial mapping.

Model calibration typically used machine-learning or regression approaches. Laamrani et al. [40], for example, demonstrated that partial least-squares regression improved prediction of soil organic matter and texture. Dhawale et al. [37] found that mid-infrared instruments predicted sand and clay content more accurately than portable mid-IR devices, whereas visible–near-infrared sensors provided the strongest estimates of clay content.

Two studies used remote sensing for soil characterization. Bouroubi et al. [36] used WorldView-2 multispectral imagery to derive soil nutrient information, while Wrozyna [47] evaluated UAV-mounted multispectral sensors for nutrient estimation. Both studies emphasized that remote sensing requires ground calibration for operational precision agriculture applications. Table 2 summarizes key data-gathering and analytical methods.

3.1.2. Thematic soil mapping

In recent years, the use of site-specific management (SSM) through variable-rate nitrogen applications has increased among government agencies and farming communities. Site-specific management typically operates within management zones, or field sub-areas that exhibit uniform soil, crop, or yield characteristics [48]. High-density sensor measurements, combined with spatio-temporal data, provide a detailed understanding of soil variability that enables accurate SSM. This review identified seven studies focused on generating thematic maps supporting site-specific management [34,48–53]. These maps included nitrogen variability maps, soil property layers, and crop health status assessments.

Remote sensing was used in three studies: Landsat (Paul et al. 2022), UAV multispectral imagery [50,52], and RapidEye imagery [48]. EMI-based proximal sensing supported zone delineation in Altdorff et al. [34]. Huang [49] evaluated multi-sensor soil maps calibrated with regression models. Most studies used machine-learning algorithms to relate sensor data to soil or crop attributes. Table 3 outlines methods used in developing thematic soil maps.

3.1.3. Soil moisture estimation

Soil moisture serves as a useful proxy for decision-making regarding irrigation. However, its high spatial and temporal variability makes large-scale measurement challenging, particularly through in situ monitoring networks [54]. In this review, eleven studies piloted DATs

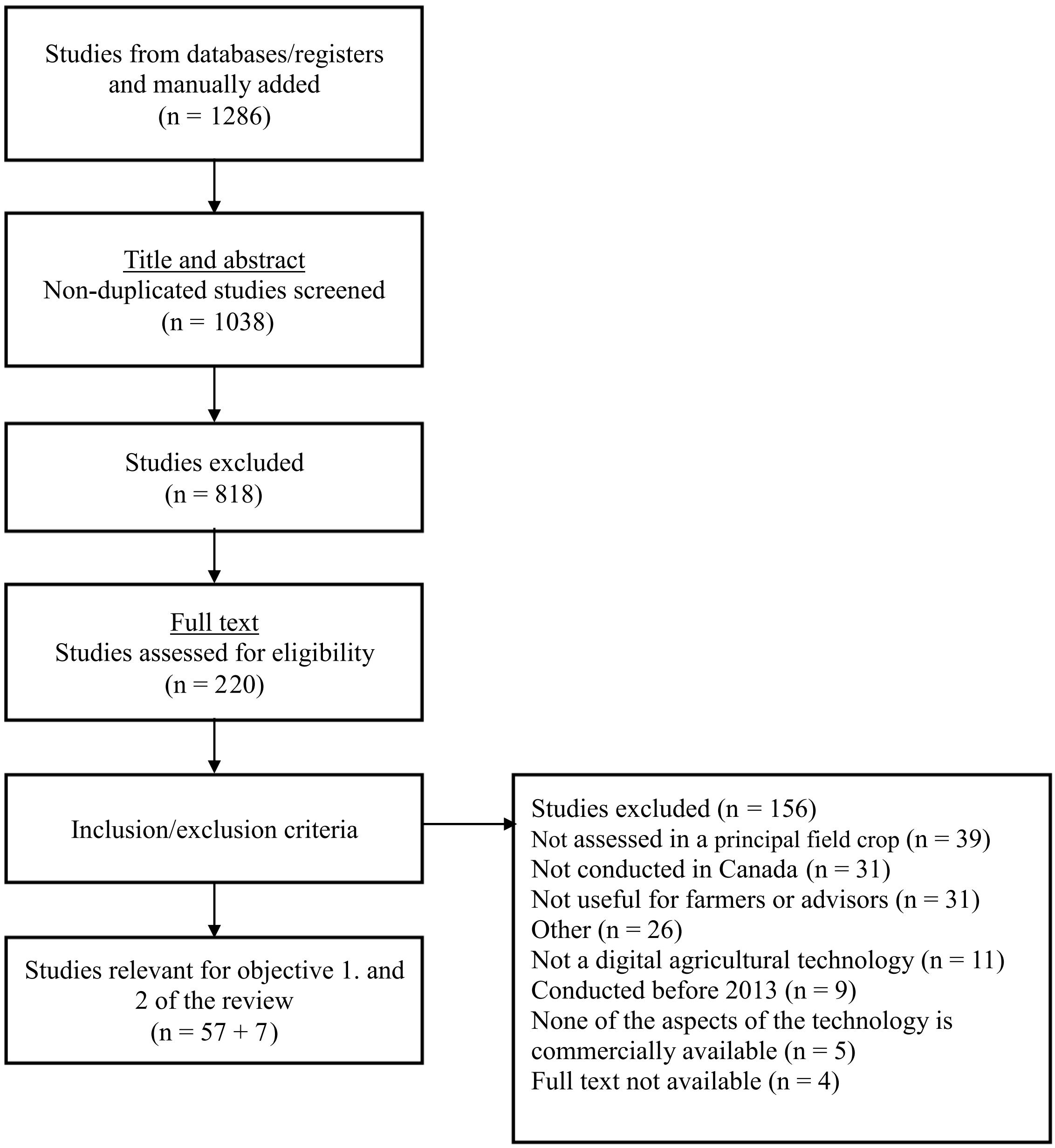

Fig. 2. Prisma flowchart of the scoping review of agricultural digital technologies developed and assessed in main crops, and barriers and motivators of different stakeholders for their adoption in Canada.

for soil moisture estimation using satellite, UAV, or hybrid remote sensing datasets [42,46,54–62].

Microwave sensors—including SMOS, Aquarius, RADARSAT-2, and Sentinel-1—were commonly used due to their sensitivity to soil moisture under diverse weather conditions [55,58]. Studies frequently compared remotely sensed moisture estimates to in situ measurements from soil monitoring networks [56,62].

Machine-learning methods such as random forests [59], deep neural networks [61], and hybrid models [54] improved predictive accuracy in many cases. Table 4 provides an overview of methods and performance metrics.

3.1.4. *Crop properties*

Remote sensing technologies, especially multispectral and hyperspectral Earth observation (EO) imaging, are used to capture spatial variability in plant growth. These methods enable early detection of crop needs such as fertilizer, irrigation, and pest control by analyzing vegetation indices like the Normalized Difference Vegetation Index (NDVI), which estimates parameters such as Leaf Area Index (LAI) and biomass. Various methods of high-resolution imagery collection such as UAV imagery, satellite, and aerial photography allow detailed monitoring at different scales. We identified seven studies used DATs to estimate crop canopy nitrogen, biomass, or leaf area index [36,42,50,63–66]. Multispectral and hyperspectral UAV imagery enabled fine-scale characterization of crop vigor, while SAR data supported biomass estimation regardless of weather conditions [65].

Machine-learning models, including Gaussian process regression [64], random forests, and multiple linear regression, were frequently applied. Bahrami et al. [63] demonstrated the effectiveness of integrating SAR polarimetry with vegetation indices for biomass and LAI estimation. Table 5 summarizes predictive approaches used in this category.

3.1.5. *Crop yield prediction*

Crop growth and development are important predictors of crop yield. Remote sensing offers an efficient option, enabling the collection of soil

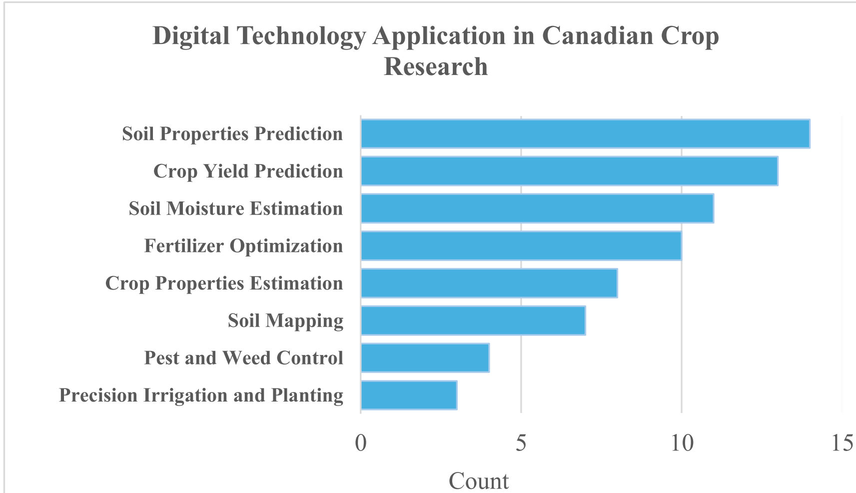

Fig. 3. Number of studies on digital technologies by application category in crop production.

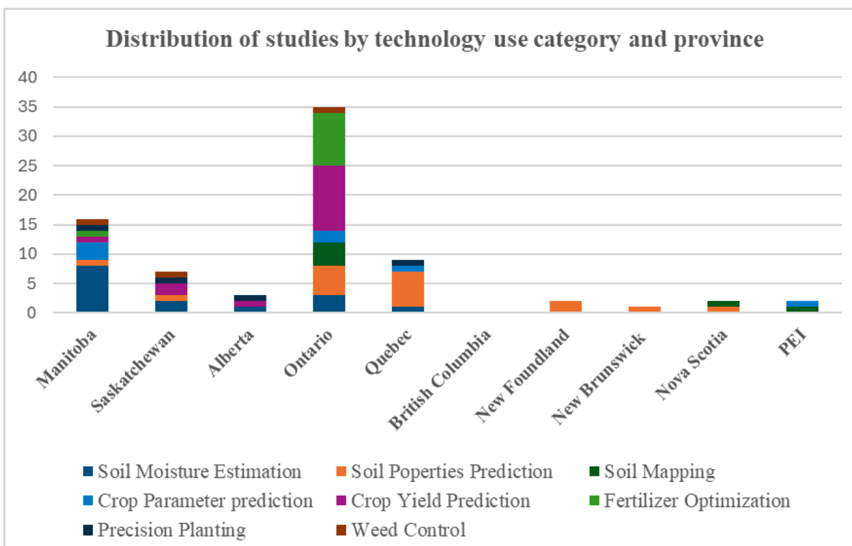

Fig. 4. Provincial Distribution of DAT Studies by Technology Application Category in Canadian Crop Production.

Table 2
Summary of studies on soil properties prediction: Crop types, data Collection techniques, and data analysis methods.

Soil properties (n = 14)	Crops			Data collection		Data analysis			
	Corn	Soybean	Wheat	Remote sensing (Satellites and RADAR)	Proximal and in-situ sensing (cellphone camera, electromagnetic induction, portable sensors, OSA, UAV)	Machine Learning	Regression methods	DSSAT Simulation	Other
	9	5	3	2	12	3	4	2	5

and crop data over vast areas. Advances in high-resolution optical sensors, such as RapidEye and Sentinel-2, which feature frequent revisit cycles, enable the fine-scale detection of spatial patterns in soil properties, crop growth, and productivity, and can even aid in yield prediction [67]. In this review, fourteen studies predicted crop yields using remote sensing, proximal sensing, simulation models, or hybrid methods [68–70,48,71–73,67,74,41,75,42,76,77].

Yield-monitoring sensors with GNSS [69,70], multispectral satellite imagery [48,72], UAV imagery [74], and lidar-derived topography [71] were common data sources.

Several studies used Decision Support System for Agrotechnology (DSSAT) models to simulate crop growth and predict yields under varying conditions [67,41,76]. Others applied machine-learning models to vegetation indices derived from Sentinel-2 or RapidEye data [75,77]. Table 6 summarizes methods and predictors.

3.1.6. *Fertilization optimization*

The most common fertilizers used in crop production are nitrogen based. Site-specific technologies have emerged to optimize the use of fertilization in fields and account for spatial heterogeneity and have a potential to reduce production costs and provide environmental benefits. Ten studies evaluated technologies aimed at improving nitrogen

Table 3
Summary of studies on thematic maps: Crop types, data collection techniques, and data analysis methods.

Thematic mapping (*n* = 7)	Crops				Data collection		Data analysis**	
	Canola	Corn	Soybean	Wheat & Barley	Remote sensing (Satellite, LiDAR)	Proximal sensing (e.g., EMI and Portable Sensors)	Machine Learning	Regression/other algorithms
	1	4	2	2	4	3	5	3

Table 4
Summary of studies on soil moisture estimation: Crop types, data collection techniques, and data analysis methods.

Soil moisture estimation (*n* = 11)	Crops					Data collection		Data analysis			
	Canola	Corn	Soybean	Wheat	Others	Remote sensing (Satellites and RADAR, L-Band radiometer)	In situ and proximal sensing (cellphone camera, in situ and portable sensors)	Machine Learning	WCM-Ulaby	Others (Regression, stability analysis, etc.)	DSSAT Simulation
	7	7	8	4	7	9	2	5	2	3	1

Table 5
Summary of studies on predicting crop properties estimation: Crop types, data collection techniques, and data analysis methods.

Crop parameters prediction (*n* = 7)	Crops			Data collection			Data analysis		
	Corn	Soybean	Wheat	Remote sensing (Satellites and RADAR, UAVs)	Proximal and in-situ sensing (Ground penetration Radars, Portable sensors and cameras)	Machine Learning	Water Cloud (WCM)-Ulaby	DSSAT Simulation	Other
	6	4	2	5	3	3	2	2	1

management [78,73,76,79–82,66,83,84].

Studies examined variable-rate versus uniform nitrogen application [73,79], machine-learning models for site-specific recommendations [82,83], and decision-support systems such as DSSAT [76]. Most studies indicated agronomic benefits, such as improved yield or reduced N losses, but few assessed economic outcomes. Table 7 details fertilizer optimization methodologies.

3.1.7. Pest and weed control

Pests and weeds add to production costs and reduce yield. Controlling them is important to prevent crop yield reduction and resulting losses. However, weed detection and precision spraying is technically challenging and technological methods for early detection and those identifying targeting specific weeds are being explored. Four studies addressed pest or weed detection using imaging systems or IoT sensors [85–87,84]. Approaches included deep neural networks for weed–crop segmentation [85], NDVI-based detection of weed patches [84], and IoT systems for pathogen monitoring [87]. These systems showed high potential but were rarely validated in commercial production settings.

3.1.8. Precision planting and irrigation

Precision planting and irrigation are critical to saving seeding costs and addressing water scarcity, respectively. We identified three studies that assessed DATs in precision planting and irrigation [88–90]. Precision planting tools included automated depth-control systems and variable-rate seeders [88,89]. Sadri et al. [90] developed a machine-learning model to forecast irrigation needs in canola and wheat, demonstrating the potential for improved water-use efficiency.

3.2. Funding sources for crop production research in Canada

Studies were concentrated in Ontario, Quebec, Manitoba, and Saskatchewan. Federal funding agencies supported most of the research, especially in eastern provinces, while provincial governments and producer groups contributed less frequently. Fig. 5 illustrates the distribution of funding across provinces.

3.3. Barriers and motivators for the adoption of digital technologies in Canada

Five studies examined producers' perspectives [28,91–94], and three examined advisors, academics, or service providers [29,95,96]. One examined government perspective [96].

Cost–benefit considerations were the most frequently reported determinant of adoption, followed by data governance concerns, perceived lack of control over data use, and internet connectivity challenges. Producers also pointed to usability and training as important factors. Advisors emphasized broader constraints, including financing, limited technical support, and difficulties integrating different digital tools and platforms. Adoption factors were grouped using the Social-Ecological Model [97]. Tables 8 and 9 summarize motivators and barriers identified in these studies from producers and advisors' perspectives, respectively.

4. Discussion

4.1. Patterns and limitations across DAT categories

Across DAT applications, several interpretive patterns emerge that help explain both the strengths and limitations of current development efforts in Canada. In soil property prediction, PSS and related analytical pipelines consistently produced strong estimates of attributes such as texture, organic matter, and nutrient content, with studies demonstrating high predictive accuracy under localized conditions [37,40]. However, these models remain highly site-specific and depend on robust calibration datasets, reflecting challenges noted globally in scaling soil sensing beyond small experimental areas [98]. Remote sensing approaches, such as those using WorldView-2 or UAV-mounted sensors [36,47], expanded spatial coverage but generally required supplementary ground-truthing. These results collectively suggest that soil-focused DATs in Canada remain technically strong but limited in cross-regional generalizability.

Similar patterns appear in thematic soil mapping and soil moisture estimation. High-density spatial data—from EMI sensors, UAV multispectral imagery, or microwave satellites such as Sentinel-1, SMOS, and AQUARIUS—enabled detailed characterizations of variability [58,48].

Table 6
Summary of studies on crop yield prediction: Crop types, data collection techniques, and data analysis methods.

Yield Prediction (n = 14)	Crops			Data collection		Data analysis				
	Corn	Soybean	Wheat	Remote sensing (Satellites and RADAR, UAVs)	Proximal and in-situ sensing (ViT transformer, portable sensors, yield monitors)	Machine Learning	Regression methods	DSSAT Simulation	Other	Water Cloud (WCM)-Ulaby
	6	4	6	6	7	3	2	6	3	1

Table 7
Summary of studies on fertilizer optimization, data collection techniques, and data analysis methods.

Fertilizer Optimization (n = 10)	Crops				Data collection				
	Corn	Canola	Wheat	Soybean	Remote sensing (Satellites and RADAR, UAVs)	Proximal and in-situ sensing (Ground penetration Radars, Portable sensors and cameras)	Machine Learning	DSSAT Simulation	Other
	4	2	2	2	02	08	3	2	5

Yet their performance still depended on environmental conditions, crop canopy interference, and the availability of ground measurements for calibration [54,99]. While combining SAR, passive radiometry, and optical sensors improved robustness across scales, long-term and multi-region validation remains rare. This has implications for irrigation planning and drought management, where producers need stable tools that perform consistently across seasons.

Similarly, crop and yield prediction studies achieved good performance with vegetation indices but faced saturation and limited cross-season generalizability [64,67,75]. Although SAR-based approaches mitigated some of these issues, most studies remained confined to plot-scale trials or single-season analyses, limiting practical deployment in commercial agriculture [63,65].

Across fertilization optimization, pest and weed detection, and precision planting, innovation gaps are even more apparent. While nitrogen management tools are widely studied due to economic and environmental considerations, most evaluations focused on agronomic performance rather than economic returns or user feasibility. Pest and weed detection research remain comparatively sparse in Canada, despite global advances in targeted spraying and machine-vision identification. LiDAR-based sprayers are in use and are effective, but advances are being made for precise spot-specific spraying using ultra sonic sensing system saving up to 40 % of agrochemical application [100]. However, these smart sprayers also need intensive field testing in various types of fields and orchard before commercialization [101]. Similarly, precision planting tools show potential for improving stand establishment, but have yet to undergo extensive on-farm validation in varied Canadian conditions.

4.2. Concentration of DAT development in early-stage sensing applications

Interpreting the findings of this scoping review through a SIS lens highlights how DATs in Canada are shaped not only by their technical performance but also by institutional structures, funding dynamics, regional disparities, and stakeholder relationships. These findings align with recent research from the United States [102] and confirm the central importance of clear, demonstrable return on investment [103].

While digitalization is often portrayed as a transformative opportunity in global reviews [13,14], our synthesis shows that DAT development and adoption in Canadian crop production remain uneven across both technological and geographic dimensions. Although many tools perform well in controlled or localized settings, few are validated across agroecological zones or integrated into producer decision-making

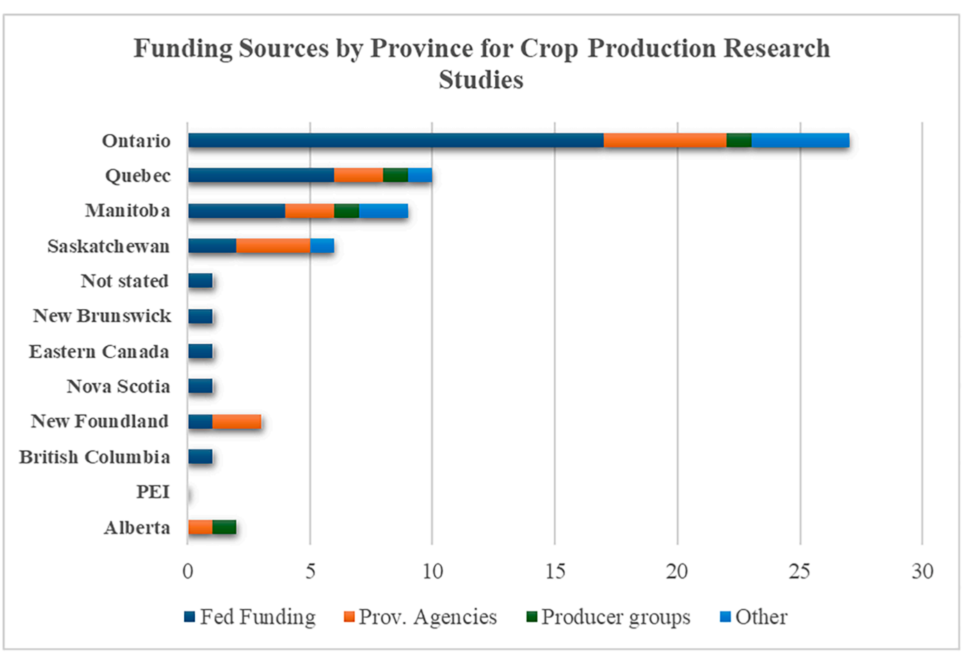

Fig. 5. Funding sources by Province for studies assessing digital technologies piloted in main crop.

Table 8
Summary of behavioral determinants influencing producers' adoption of digital agricultural technologies.

Determinants		
Individual-Level	Relational (Interpersonal)	Contextual and Structural
1. Cost–benefit belief ($n = 5$) 2. Perceived control ($n = 3$) 3. Coping capacity ($n = 3$) 4. Lack of knowledge ($n = 3$) 5. Perceived practicality ($n = 2$) 6. Emotions (e.g., fear of losing data, frustration) ($n = 2$) 7. Perceived quality of data ($n = 1$) 8. Data-informed decision support ($n = 1$) 9. Farmer personality traits (e.g., stubbornness, openness to novelty) ($n = 1$) 10. Age of farmer ($n = 1$) 11. Use of other technologies ($n = 1$) 12. Perceived time savings ($n = 1$) 13. Job satisfaction ($n = 1$) 14. Perceived risk ($n = 1$)	1) Producer–university/research partnerships ($n = 2$) 2) Farmer–landowner relationship ($n = 1$) 3) Farmer–private company relationship ($n = 1$) 4) Farmer–advisor relationship ($n = 1$) 5) Reputation with peers and others ($n = 1$)	• Data security concerns ($n = 4$) • Government policy and legislation ($n = 3$) • Internet connectivity ($n = 2$) • Accessibility and compatibility between technologies ($n = 2$) • Lack of implementation guidelines ($n = 2$) • Limited financing options ($n = 2$) • Crop marketing challenges ($n = 1$) • Broader digitalization trends ($n = 1$) • Environmental sustainability goals ($n = 1$) • Desire to increase market share ($n = 1$) • Organizational or cultural resistance ($n = 1$) • Contractual limitations ($n = 1$) • Failed implementation in comparable businesses ($n = 1$) • Lack of organizational leadership ($n = 1$) • Underutilization of collected data ($n = 1$)

*Many of these behavioral determinants were associated with both adoption and non-adoption decisions, depending on the specific context.

contributing to slow progression toward commercial maturity.

Most DAT studies focused on proximal and remote sensing for estimating soil properties, moisture, crop status, or yield. This reflects a strong research base in sensor calibration, image processing, and machine learning—patterns consistent with international evidence showing that sensing technologies dominate early-stage digital agriculture innovation [104,17]. Although many studies reported high predictive accuracy, they often relied on controlled environments or small datasets, limiting scalability. This reflects broader patterns in digital agriculture: innovation efforts anchored in sensing and model accuracy often struggle to deliver decision-ready tools without corresponding investments in calibration data, advisory capacity, and regionally distributed trials. The uneven maturity of DAT categories also suggests a misalignment between research activity and producer priorities, with likely implications for adoption and the long-term trajectory of digital transformation.

4.3. Sensing pipelines and innovation maturity

Across soil, crop, and yield applications, a clear methodological pattern emerges most Canadian DAT studies rely on a sensing–analytics pipeline, wherein proximal or remote sensing data are processed using statistical or machine-learning models before accuracy is reported. This pattern is common in global digital agriculture research [104,14] and enables rapid technical iteration but also constrains innovation maturity.

Table 9
Summary of behavioral determinants identified in advisors' perspectives on the adoption of digital agricultural technologies.

Determinants		
Individual-Level	Relational (Interpersonal)	Contextual and Structural
1. Cost–benefit belief ($n = 2$) 2. Perceived control ($n = 1$) 3. Data-informed decision support ($n = 1$) 4. Perceived practicality ($n = 1$) 5. Perceived time and labour savings ($n = 1$) 6. Coping capacity ($n = 1$) 7. Lack of knowledge ($n = 1$) 8. Farmer personality traits (e.g., stubbornness, openness to novelty) ($n = 1$) 9. Age of farmer ($n = 1$)	1. Producer–university/research relationships ($n = 1$) 2. Farmer–landowner relationship ($n = 1$)	• High initial investment costs ($n = 3$) • Internet connectivity limitations ($n = 2$) • Data security and privacy concerns ($n = 2$) • Limited financing options ($n = 2$) • Need for training ($n = 2$) • Lack of technical support ($n = 2$) • Compatibility and accessibility issues across technologies ($n = 2$) • Difficulty in demonstrating return on investment ($n = 1$) • Rapid technology turnover ($n = 1$) • Government policy and regulation ($n = 1$) • Misalignment between regenerative and digital agriculture ($n = 1$) • Organizational or cultural resistance ($n = 1$) • Underutilization of collected data ($n = 1$) • Lack of trust in technology providers ($n = 1$)

*These behavioural constructs reflect both perceived enablers and barriers to adoption, as viewed by advisors supporting farmers in the implementation of digital technologies.

Decision-support systems and process-based models showed promise yet were applied far less frequently, and often lacked the localized agronomic datasets needed for effective calibration [67,76]. Some tools, such as Western Ag's PRS Cropcaster®, incorporate financial data to inform economic decision-making [105,106]. Commercial DSSs typically feature user-friendly interfaces that provide graphical and numerical outputs. However, their accuracy and utility depend on access to large, high-quality datasets and validation across crops, varieties, and environmental conditions. In many cases, DSSs reviewed in this study remain at the pilot stage, with limited testing across diverse farm settings [67,41,76,80]. Meanwhile, areas of major producer concern such as pest, weed, and disease detection remain underrepresented in Canadian research relative to global innovation trends.

Together, these patterns indicate that Canada's DAT research landscape is technically strong but highly fragmented, with limited integration across sensing, modelling, and decision-support layers. This fragmentation helps explain persistent adoption barriers and the slow evolution from prototypes to regionally validated commercial tools.

4.4. Role and evolution of AI

AI, primarily in the form of machine learning and deep learning, plays a central role in contemporary DAT development in Canada. Most AI applications focus on prediction tasks, including soil properties, soil moisture, biomass, and yield estimation, often demonstrating high accuracy under specific conditions. However, these models frequently rely on large, well-curated datasets and exhibit limited generalizability beyond the contexts in which they are trained. Few studies address model interpretability, transparency, or integration into actionable decision-support systems. As AI-driven tools increasingly influence farm management decisions, issues of explainability, validation standards, and advisory mediation become critical. Without these safeguards, AI risks reinforcing experimental success without delivering decision-ready tools for producers.

4.5. Geographic mismatch between research activity and production landscapes

A notable structural finding is the disproportionate concentration of federally funded DAT research in eastern Canada, despite western provinces accounting for the majority of national crop production. This spatial misalignment reflects broader structural patterns in Canada's ag-tech ecosystem [18], where firms, research institutions, and innovation funding tend to cluster around major metropolitan centres rather than primary production regions. A similar imbalance has been documented in national efforts to develop carbon emissions estimation methodologies, reinforcing concerns about misalignment within Canada's research funding and innovation system [107].

Limited piloting and validation in high-production regions constrains cross-regional model robustness, weakens on-farm relevance, and slows technology diffusion. Within a SIS perspective, this represents a coordination failure between research and development, end users, and public funders. The implications are significant for both technology performance and adoption. Canada's agroecological heterogeneity, including variation in soils, climate, cropping systems, and farm scale, limits the transferability of DATs validated in narrow or non-representative settings. Concentrating research activity outside major production regions further reduces opportunities for producer engagement, feedback, and integration with advisory services. Together, these findings point to a clear need for regionally distributed validation trials and innovation infrastructure that better reflect Canada's production geography.

4.6. Limited attention to stakeholder perspectives beyond producers

Only a small share of studies captured the perspectives of advisors, agronomists, service providers, or policymakers despite evidence that these actors play a central role in digital adoption. Advisors are often key intermediaries in interpreting sensor outputs and integrating DATs into farm decision-making [95,108]. Their identification of barriers such as interoperability issues, insufficient training, limited technical support, and connectivity gaps suggests systemic challenges that extend beyond producers' individual preferences. This aligns with international research emphasizing the importance of advisory and extension capacity in digital transformation [16,17]. Moreover, given that advisors work more closely with small- and medium-scale producers who face steeper barriers to adoption, their inclusion is essential to ensuring that digitalization does not accelerate consolidation or exacerbate inequality in the agricultural sector [109–111].

4.7. Persistent concerns around data governance and producer autonomy

While data governance, privacy, and security are increasingly recognized as central to digital agriculture adoption, empirical evidence on these issues remains limited within Canadian DAT research. Much of the technical literature treats data primarily as an input to modelling and analytics pipelines, with little attention to questions of ownership, consent, interoperability, or long-term stewardship. In contrast, stakeholder-focused and perception-based studies consistently highlight concerns around data control, trust in technology providers, and uncertainty over how farm-level data may be reused or monetized. Across these studies, cost–benefit considerations remain the strongest predictor of adoption, but concerns related to data ownership, privacy, and loss of control recur as significant secondary constraints.

These governance challenges function as system-level barriers that shape adoption decisions independently of technical performance. As digital agriculture increasingly relies on artificial intelligence and platform-based analytics, the absence of clear, transparent, and enforceable data governance frameworks may further limit producer willingness to engage with DATs. These concerns reflect broader global debates about data power asymmetries between producers and ag-tech firms [21], where farmers often have limited negotiating power in relationships with large platforms that collect, aggregate, and monetize farm-level data.

Although emerging industry-led initiatives such as Ag Data Transparent and open-source interoperability frameworks like ADAPT and ISOBUS offer partial solutions, formal policy mechanisms in Canada remain underdeveloped. Proposed responses include dividend-based compensation models that share profits derived from data use, as well as farmer cooperatives that negotiate collective data agreements to protect raw data and improve bargaining power [112]. Leading firms such as John Deere have begun engaging with these initiatives, signaling a gradual shift away from closed, proprietary data models toward more open and transactional data ecosystems. While these developments are promising, targeted policy intervention remains necessary to reduce uncertainty, strengthen trust, and ensure equitable access as digital agriculture continues to scale.

4.8. Implications from the SIS perspective

Applying a SIS lens reveals four structural barriers:

1. Dominance of public funding, which emphasizes research outputs over commercial readiness;
2. Fragmented coordination between federal and provincial programs, contributing to regional imbalances;
3. Limited private-sector investment, constraining commercialization;
4. Underdeveloped data governance, limiting producer trust and adoption.

These challenges reflect system-level misalignments rather than isolated technical shortcomings. Improving coordination among researchers, funders, advisors, and technology firms is therefore essential to enable responsible, effective, and equitable digital transformation in agriculture.

While Canada's production systems and policy environment are distinctive, the patterns identified in this study are not unique. Challenges such as site-specific performance of DATs, the need for regional calibration, ongoing data governance concerns, uneven commercialization pathways, and limited advisory capacity are consistently reported across high-income agricultural economies. Canada's adoption trajectory is broadly comparable to peer jurisdictions, though important structural differences remain. In the United States, precision agriculture adoption is more extensively documented and more widespread on large row-crop farms, whereas Canada's national evidence base remains fragmented. Similar constraints related to farm scale, advisory capacity, data governance, and the diffusion of advanced digital tools have been documented in the European Union, Australia, and New Zealand. Taken together, these parallels indicate that the Canadian experience reflects common systemic constraints in digital agriculture adoption rather than country-specific limitations, and that insights from this case are relevant to other jurisdictions navigating transitions toward data-driven and sustainability-oriented agricultural systems.

5. Policy recommendations

Findings from this scoping review highlight several structural levers that can support the responsible development, validation, and adoption of DATs in Canada. The following recommendations draw on the SIS perspective to identify interventions that address technological gaps, institutional constraints, and regional inequities.

5.1. Strengthen coordination across the innovation ecosystem

Canadian DAT development is shaped by fragmented funding landscapes and uneven regional research activity. Coordinated mechanisms—such as joint federal–provincial funding programs, cross-provincial testbeds, and structured partnerships among universities, advisors, producer groups, and technology firms—would ensure that technology development aligns with producer needs across diverse agroecological regions. Integrating RRI principles, as recommended by Ebrahimi et al. [16], can promote early inclusion of stakeholders and improve the social relevance of digital tools.

5.2. Align research funding with production geography

Given the geographic mismatch between where most DAT research occurs and where most crop production takes place, targeted funding should support technology development, piloting, and validation in western Canadian provinces. Priority areas include field-scale trials of sensing technologies, calibration studies across soil zones, and region-specific performance assessments of DSSs. These steps would reduce uncertainty for producers and improve the generalizability of research findings.

5.3. Increase support for commercialization and private-sector collaboration

Canada's ag-tech landscape is dominated by small firms with limited capital and commercialization capacity. Federal and provincial governments can accelerate innovation by expanding programs that support commercialization pathways, such as innovation vouchers, tax credits for digital agriculture R&D, matching funds for venture capital, and multi-year public private partnerships. Strengthening links between academic researchers and private firms can help translate prototypes into market-ready tools.

5.4. Expand training, advisory capacity, and digital extension

As key intermediaries, agronomists and advisors play a critical role in helping producers interpret complex datasets and use decision support tools effectively. Targeted investments in digital extension, including training programs, certification pathways, and dedicated advisory networks, would strengthen capacity across regions. Ensuring that small and medium scale producers have equitable access to technical support is essential to avoid reinforcing existing structural inequities within the sector.

5.5. Foster region-specific DSS development and validation

Decision-support systems have high potential for enabling site-specific management yet to remain underdeveloped relative to sensing technologies. Funding should prioritize DSS projects that incorporate local agronomy, integrate multiple data streams, and undergo iterative user testing with producers and advisors. Open, modular DSS architectures should be encouraged to reduce the burden of system integration and improve long-term adoption.

5.6. Embed responsible innovation principles in digital agriculture strategy

An RRI approach encourages anticipation of unintended consequences, reflection on ethical and distributive implications, and ongoing stakeholder engagement. Integrating RRI into federal and provincial digital agriculture strategies can help ensure that digitalization serves broader societal goals, including environmental sustainability, producer autonomy, and rural development.

6. Conclusion

This scoping review synthesizes a decade of research on DATs developed, piloted, or validated in Canadian crop systems and examines the social and institutional factors shaping their adoption. The findings reveal a landscape characterized by strong technical innovation, particularly in sensing and prediction, but limited commercial readiness, uneven geographic distribution of research, and persistent concerns related to data governance and producer autonomy.

Applying a Sectoral Innovation Systems lens highlights how these challenges stem from broader structural features of Canada's digital agriculture ecosystem, including fragmented funding pathways, limited private sector investment capacity, and weak mechanisms for cross-regional validation. Although Canada is often portrayed as a global leader in digital agriculture, the empirical evidence needed to substantiate these claims, particularly on economic outcomes, large-scale adoption, and environmental performance, remains limited.

At the same time, the Canadian case offers important insights for other countries navigating digital transformation in agriculture. The need for regionally calibrated technologies, robust data governance frameworks, long-term advisory support, and inclusive innovation processes is not unique to Canada; rather, these issues resonate across high-income, export-oriented agricultural economies. By identifying the current strengths and constraints of Canada's digital innovation system, this review provides an evidence base for designing policies that support responsible, equitable, and efficient integration of DATs into crop production.

Future research should build on these findings by expanding multi-year, on-farm validation studies; systematically assessing economic returns and environmental outcomes; and examining adoption patterns over time. Strengthening coordination among researchers, advisors, industry, and policymakers will be essential for ensuring that digital agriculture contributes meaningfully to Canada's productivity, competitiveness, and sustainability goals.

CRediT authorship contribution statement

Hanan Ishaque: Writing – review & editing, Writing – original draft, Formal analysis, Conceptualization. **V. Margarita Sanguinetti:** Writing – review & editing, Validation, Data curation. **Francine Nelson:** Data curation. **Heather Ganshorn:** Data curation. **Guillaume Lhermie:** Writing – review & editing, Supervision, Resources.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.atech.2026.101820.

Data availability

Data will be made available on request.

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