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# Emerging Digital Technologies in Indian Agriculture: Adoption, Applications, Benefits, and Future Directions

Ahesanali S. Dadavala[1], Biren M. Patel[2], Sirajali A. Nagalpara[3]

[1] *Ph.D. Scholar, Dept. of Computer Science, H.N.G. University, Gujarat, India*
[2] *Associate Professor, Dept. of Computer Science, H.N.G. University, Gujarat, India*
[3] *Assistant Professor, I.T. Sheliya Jafri BCA College, H.N.G. University, Gujarat, India*

**Abstract** —*Indian agriculture, which sustains the livelihoods of over 150 million farmers, is undergoing a rapid digital transformation driven by Artificial Intelligence (AI), the Internet of Things (IoT), and allied smart-farming technologies. This paper presents a concise review examining which digital technologies are being adopted across Indian agriculture during 2025-2026, how they function, and what benefits and limitations they present. The review method involved a structured, non-systematic scoping of peer-reviewed journal articles, conference papers, and government reports published mainly between 2021 and 2026, covering thirteen technology domains spanning AI, IoT, precision agriculture, drones, remote sensing, machine learning, computer vision, robotics, big data, cloud/edge computing, smart irrigation, blockchain, and the emerging Agriculture 5.0 paradigm. The results show that adoption is most advanced where technologies address acute, visible constraints such as water scarcity and fragmented field geometry, with documented outcomes including 20-35% water savings from smart irrigation and yield gains of up to 40% from AI-driven advisory programs. Comparative analysis further indicates that capital-intensive technologies such as robotics and blockchain remain concentrated among commercial farms, while low-cost sensing and AI-advisory tools have achieved broader smallholder reach. The discussion highlights that persistent barriers-fragmented landholdings, rural connectivity gaps, and limited digital literacy-continue to constrain equitable, nationwide scale-up, and identifies Edge AI, digital twins, explainable AI, and autonomous farming as priority directions for future development.*

***Keywords***—*Digital Agriculture, Artificial Intelligence, Internet of Things (IoT), Precision Agriculture, Agriculture*

## I. INTRODUCTION

Agriculture remains the backbone of the Indian economy, providing livelihoods for more than 150 million farmers and underpinning national food security [1]. Indian farming nonetheless faces compounding pressures: fragmented and shrinking landholdings, groundwater depletion, climate variability, and a widening gap between input costs and farm-gate prices. Digital transformation-broadly understood as the integration of sensing, connectivity, and intelligent analytics into agricultural decision-making-has emerged as a central strategy for addressing these pressures while improving productivity and farmer incomes [2].

The need for smart farming in India is particularly acute given the country's agroecological diversity and the predominance of smallholder farms, which demand low-cost, scalable, and locally adapted digital solutions rather than the capital-intensive systems common in large-farm economies [3]. Recent national initiatives, including the Digital Agriculture Mission, the AgriStack farmer-data ecosystem, and multilingual AI advisory tools such as Kisan e-Mitra, signal strong policy commitment to this transition.

The core question motivating this review is straightforward: which digital technologies are currently being adopted in Indian agriculture, how do they function, and what benefits, limitations, and future prospects do they present? Rather than conducting an exhaustive systematic literature review, this paper provides a concise, up-to-date overview intended to orient researchers, practitioners, and policymakers to the current state of AI- and IoT-driven smart farming in India.

## II. LITERATURE REVIEW

The literature on AI and IoT-enabled agriculture has grown rapidly between 2021 and 2026, with review-level syntheses documenting a marked acceleration in publication output as low-cost sensing hardware and cloud-based analytics platforms have matured [4]. A parallel and increasingly India-relevant strand of this literature specifically tracks the convergence of AI and IoT into unified "AIoT" systems, noting that studies explicitly integrating both technologies, rather than treating them in isolation, have become dominant only since 2021 [5]. This section critically compares recent studies across the major technology domains reviewed in this paper, identifies recurring strengths and limitations, and concludes by situating the specific gap this paper addresses.

Within the AI and precision-agriculture literature, recent reviews consistently report strong technical performance for machine-learning-based advisory and prediction systems under controlled or curated conditions [6]. A comprehensive review of smart-sensing technologies for AI-integrated agriculture similarly documents sharp publication growth in 2023 and 2024, attributing this trend to advances in low-power IoT devices and cloud analytics infrastructure

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[7]. However, a recurring limitation across this body of work is that reported accuracy figures are rarely validated against the heterogeneous field conditions, mixed cropping patterns, and regional crop-variety diversity characteristic of Indian farms, leaving a persistent gap between laboratory-reported performance and real-world reliability.

IoT-specific studies focused on Indian agriculture show a complementary but distinct trend: rather than emphasizing algorithmic accuracy, this literature emphasizes field-deployment outcomes such as water-use efficiency and yield response [8]. Machine-learning-enabled soil-nutrient monitoring and recommendation systems extend this deployment-oriented focus by coupling IoT sensing directly with automated fertilizer guidance [9]. The strength of this literature lies in its practical, outcome-oriented framing; its principal limitation is that most reported field trials remain small in scale and geographically concentrated in a limited number of states, constraining the generalizability of documented water- and yield-efficiency gains across India's diverse agroecological zones.

Studies on drones, remote sensing, and computer vision reveal a third trend: rapid growth in dataset creation and sensor-platform development, often outpacing corresponding operational deployment research. Newly released Indian UAV and leaf-image datasets provide valuable annotated resources for crop-health and pest-detection model development [10], while parallel multispectral and RGB dataset efforts support multi-stage crop monitoring specifically within Indian field conditions [11]. Broader reviews of drone-based sensing in agriculture confirm this dataset-centric emphasis, cataloguing sensor types and image-processing pipelines in considerable technical depth [12]. The corresponding limitation is that comparatively few of these studies report sustained, multi-season operational use by farmers themselves, meaning that dataset and algorithmic maturity has not yet been matched by evidence of routine field adoption.

The literature on robotics, blockchain, and Agriculture 5.0 remains comparatively early-stage. Systematic quantitative reviews of AI and robotics research report substantial growth in publication volume over the past decade, with computer vision and autonomous perception identified as central enabling techniques [13]. Conference-level reviews specific to Indian venues similarly catalogue emerging robotics and automation applications [14]. In parallel, blockchain-based agricultural supply-chain studies demonstrate technical feasibility for provenance tracking [15], while survey-based adoption research indicates that trust and regulatory compliance, rather than technical performance, are the primary barriers to uptake [16]. Across all three domains, a common limitation is the scarcity of large-scale, real-world validation studies, with most contributions remaining conceptual, laboratory-based, or limited to small pilot deployments. Conceptual work tracing the evolution from Agriculture 1.0 to Agriculture 5.0 further indicates that human-centric and sustainability-oriented principles remain underrepresented relative to purely technical automation research [17].

Taken together, this body of literature reveals a consistent pattern: existing reviews are predominantly technology-siloed, each examining a single domain such as IoT sensing, drone-based remote sensing, or blockchain traceability in isolation, and few provide an integrated, cross-technology synthesis specific to the Indian agricultural context during the most recent 2025-2026 period. Moreover, where India-specific evidence exists, it is unevenly distributed: water-management and AI-advisory technologies are relatively well documented through field trials, whereas robotics, blockchain, and Agriculture 5.0 remain largely conceptual. This paper addresses this gap by providing a concise, integrated overview that synthesizes current evidence across thirteen interrelated digital agriculture technology domains within a single, India-focused framework, explicitly highlighting where field-level evidence is strong and where it remains preliminary.

## III. METHODOLOGY

This review followed a structured, non-systematic scoping approach rather than a formal PRISMA-based systematic review protocol, consistent with its stated aim of providing a concise topical overview rather than an exhaustive synthesis. We identified source material through targeted searches of Scopus-indexed journals, IEEE Xplore conference proceedings, ScienceDirect, MDPI, Springer Nature, and Wiley publications, supplemented by Indian government press releases and policy documents where primary technical literature was unavailable.

The search prioritized peer-reviewed articles published between 2021 and 2026, with an explicit emphasis on studies reporting Indian case studies, field trials, or India-specific technology deployments wherever available. Thirteen technology domains were selected a priori based on their prominence in current Indian agri-tech policy and research discourse: Artificial Intelligence, the Internet of Things, Precision Agriculture, Drones (UAVs), Remote Sensing and GIS, Machine Learning and Deep Learning, Computer Vision, Robotics and Automation, Big Data Analytics, Cloud and Edge Computing, Smart Irrigation Systems, Blockchain, and Agriculture 5.0.

For each domain, information was extracted on the underlying working principle, representative agricultural applications, reported advantages and limitations, and at least one recent (2021-2026) research or field-deployment example. Extracted findings were then synthesized into a comparative analysis table (Table 1) evaluating applications, benefits, and challenges across all thirteen domains, and organized into conceptual diagrams depicting the overall digital agriculture ecosystem, the Agriculture 5.0 framework, and the data-decision flow linking sensors, drones, cloud

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computing, and farmers. No human participants, primary data collection, or experimental procedures were involved in this review; all reported findings are drawn from previously published secondary sources.

## IV. RESULT

This section presents the technologies identified through the review process, organized into thirteen domains that collectively constitute the digital agriculture ecosystem shown in Figure 1. These technologies function as interdependent layers-sensing, connectivity, intelligence, and action-that together enable data-driven farm management across Indian agriculture during 2025-2026.

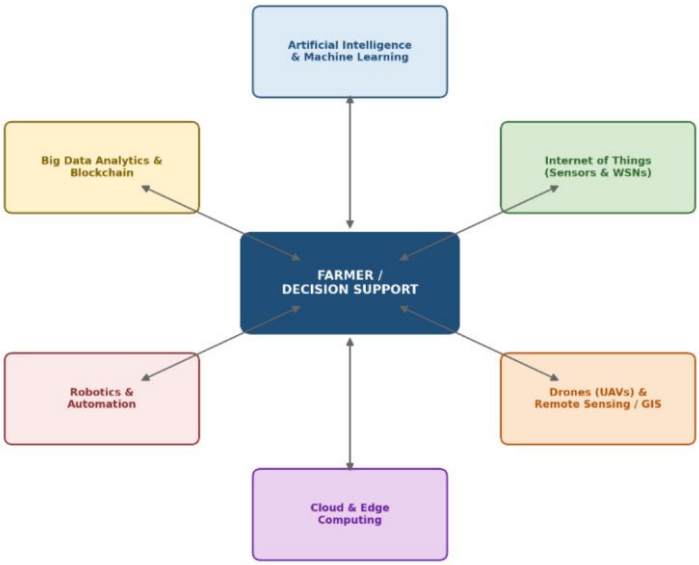



***Figure 1. The Digital Agriculture ecosystem***

### A. Artificial Intelligence and Machine Learning

Artificial intelligence has moved from pilot demonstration to routine farmer-facing deployment in India during 2025- 2026, most visibly through multilingual advisory chatbots that translate agronomic knowledge into locally accessible guidance. The Kisan e-Mitra platform, for instance, had answered over 93 lakh farmer queries as of December 2025, illustrating the scale at which AI-based advisory has begun reaching smallholders directly through mobile devices. Machine learning and deep learning models underpin much of this advisory capability, learning statistical patterns from weather, soil, and market data to generate yield forecasts, pest-risk alerts, and personalized input recommendations; AIoT-based soil-nutrient analysis systems exemplify this integration by combining sensor data with machine-learning-driven fertilizer recommendations tailored to individual fields. Complementary IoT-enabled crop-recommendation systems report improved recommendation accuracy over static, table-based fertilizer guidelines when machine learning is applied to real-time soil-nutrient data [18]. Despite these gains, model reliability remains sensitive to the diversity of Indian cropping systems, and accuracy achieved on curated datasets does not always transfer directly to field conditions with variable lighting, mixed cropping, or regional crop-variety differences.

### B. Internet of Things and Precision Agriculture

IoT sensor networks now form the backbone of precision-agriculture deployments across several Indian states, continuously monitoring soil moisture, temperature, and microclimate variables to trigger automated irrigation and fertilization decisions. Field implementations spanning Maharashtra vineyards and Punjab's rice-wheat systems have documented water savings of 20-35% alongside yield improvements of 10-20% when IoT-guided precision management replaces calendar-based scheduling. Precision agriculture's site-specific management approach-varying fertilizer, water, and pesticide application according to localized field conditions rather than uniform treatment-has attracted substantial Indian research attention, with bibliometric analysis identifying India among the leading contributing and most-cited countries globally in IoT-enabled precision-agriculture research between 2019 and 2024. Cloud and edge computing increasingly underpin these deployments: edge-based processing enables real-time irrigation control to continue operating despite intermittent rural connectivity, while cloud platforms aggregate multifarm data to support centralized advisory dashboards. Nonetheless, sensor calibration drift, battery maintenance in remote fields, and the high upfront cost of GNSS-guided equipment continue to restrict precision-agriculture adoption largely to better-resourced or commercially oriented farms.

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### C. Drones, Remote Sensing, and Computer Vision

Unmanned aerial vehicles have become an increasingly practical tool for Indian farmers managing fragmented landholdings, offering centimeter-scale imagery unattainable from satellite platforms. Multispectral and RGB drone payloads are now used to compute vegetation indices such as NDVI for crop-health and nitrogen-status assessment, supporting targeted rather than blanket agrochemical application. Newly released Indian datasets, including a multi-season UAV and leaf-image dataset for soybean crop-health and pest annotation and a multi-stage multispectral and RGB dataset for paddy monitoring jointly developed by IIT Tirupati and an agri-drone technology partner, illustrate the growing technical maturity of India-specific UAV remote sensing. Broader reviews of drone-based sensing confirm this trend, cataloguing the sensor types and image-processing pipelines underlying such deployments. Computer vision, applied both to drone imagery and to smartphone photographs, enables low-cost, scalable disease and pest identification directly in farmers' fields; bibliometric analysis identifies computer vision as the second most frequently studied technique in agricultural AI-robotics literature, accounting for up to nearly a third of publications in some databases. However, satellite revisit frequency and cloud-cover occlusion during the monsoon season continue to constrain the temporal resolution of India's key kharif cropping window, and computer-vision models trained on non-Indian datasets often generalize poorly to local field conditions.

### D. Robotics, Automation, and Big Data Analytics

Agricultural robotics-spanning autonomous tractors, robotic weeders, and precision spraying platforms-has begun appearing in Indian custom-hiring service centers, where shared-ownership models offset the high capital cost that otherwise restricts adoption to large commercial operations. Indian conference-level research has specifically examined the integration of AI and robotics within agricultural automation workflows, highlighting reduced labor dependency and more precise, consistent field operations as key benefits. Big data analytics complements this automation by aggregating sensor, imagery, market, and weather data streams at a scale unattainable through traditional survey-based agricultural statistics; bibliometric analysis of precision-agriculture research reports a 47.58% annual growth rate in IoT- and big-data-related agricultural publications between 2019 and 2024, with China and India together accounting for 62% of global publication output in this field. Integration with national data platforms such as AgriStack is expected to further extend big data analytics into policy-level planning, though data interoperability across heterogeneous government and private sources, together with farmer data-privacy concerns, remain unresolved practical challenges.

### E. Blockchain and Agriculture 5.0

Blockchain-based traceability systems are being explored across Indian agricultural supply chains to record seed provenance, dairy authentication, and direct farmer-to-market transactions on tamper-resistant distributed ledgers. A blockchain- and convolutional-neural-network-based supply-chain management system has been proposed to combine transparent transaction recording with automated quality verification for Indian agricultural produce, while survey-based adoption research indicates that farmer and stakeholder trust, alongside regulatory compliance, are more significant determinants of uptake than the underlying technology's technical performance.

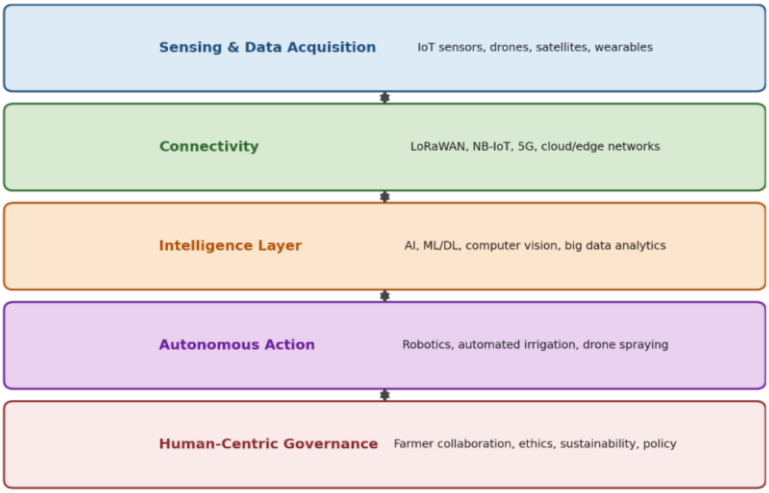



***Figure 2. Agriculture 5.0 Framework***

These traceability efforts, together with the broader integration of AI, IoT, and robotics under explicit sustainability and farmer-inclusion objectives, are increasingly discussed under the emerging Agriculture 5.0 paradigm, illustrated in Figure 2. Agriculture 5.0 extends the automation-centric Agriculture 4.0 model by emphasizing human-centric governance and agroecological sustainability alongside continued technological automation; recent conceptual

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work tracing this evolution notes the progressive integration of IoT-connected devices with AI and robotics as central to this transition. Operational Agriculture 5.0 implementations nonetheless remain nascent in India, with empirical studies validating its human-centric and equity principles still limited relative to purely technical automation research.

**F. Synthesis of Documented Impact**

Figure 3 consolidates the quantitative field-level outcomes reported across the technologies reviewed above, highlighting smart irrigation's documented 20-35% water savings and 10-20% yield gains alongside the yield increases of up to 40% reported in AI-driven advisory pilots such as Project Farm Vibes in Baramati, Maharashtra. These figures indicate that the most concrete, measurable productivity and sustainability impacts to date have come from technologies that directly target water-use efficiency and low-cost advisory delivery, rather than from more capital-intensive automation technologies, which remain earlier in their Indian adoption trajectory.

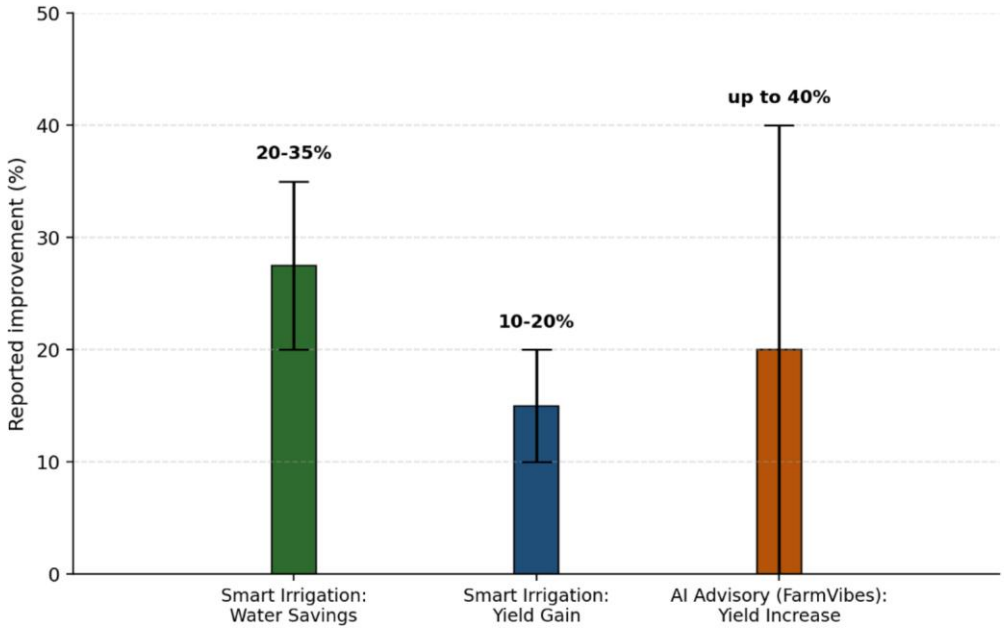



***Figure 3. Field-Level Impact of Digital Technologies.***

**G. Comparative Analysis**

Table 1 consolidates the applications, benefits, and challenges of the thirteen technologies identified above, enabling direct cross-technology comparison.

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***Table 1. Comparative analysis of digital technologies transforming Indian agriculture.***

| Technology | Main Applications | Benefits | Challenges |
|---|---|---|---|
| Artificial Intelligence | Crop advisory, yield/price forecasting, pest risk prediction | Personalized, scalable, multilingual advisory | Data scarcity; limited farmer trust/interpretability |
| Internet of Things | Soil/microclimate monitoring, automated irrigation triggers | Continuous, granular real-time field data | Sensor calibration drift; rural connectivity gaps |
| Precision Agriculture | Variable-rate input application, yield mapping | Reduced input waste, improved resource efficiency | High upfront cost for smallholder farms |
| Drones (UAVs) | Crop-health/NDVI mapping, targeted spraying | Ultra-high-resolution, on-demand imagery | Airspace regulation; battery/flight-skill limits |
| Remote Sensing & GIS | Regional crop monitoring, insurance verification | Scalable farm-to-national monitoring | Monsoon cloud cover limits satellite revisit |
| ML & Deep Learning | Disease/pest classification, nutrient recommendation | High accuracy on image/pattern-based tasks | Poor generalization to diverse Indian field conditions |
| Computer Vision | Automated disease ID, weed-crop discrimination | Low-cost, smartphone-based diagnosis | Sensitive to lighting, background, occlusion |
| Robotics & Automation | Autonomous weeding, seeding, spraying | Reduced labor dependency, precise operation | High capital cost; limited rural service infrastructure |
| Big Data Analytics | Market/yield forecasting, policy planning | Insights at scale unattainable via surveys | Data interoperability and privacy concerns |
| Cloud & Edge Computing | Real-time irrigation control, on-device diagnostics | Resilient operation despite connectivity gaps | Edge device compute/power constraints |
| Smart Irrigation | Automated drip/sprinkler scheduling | 20-35% water savings, 10-20% yield gains | Cost; reliable rural power/solar backup needed |
| Blockchain | Seed/input traceability, supply-chain transparency | Reduced fraud, improved price transparency | Requires disciplined data entry; trust gap risk |
| Agriculture 5.0 | Integrated, sustainability-oriented farm management | Human-centric, resilient, equitable technology use | Nascent implementation; limited empirical validation |

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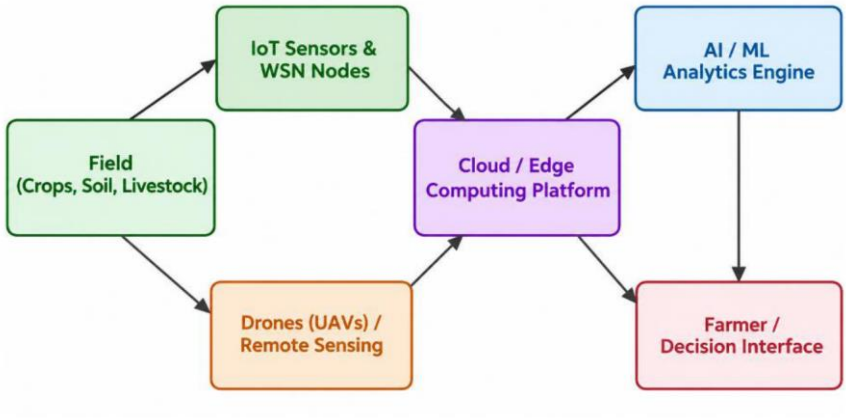



***Figure 4. Smart Farming Data Flow.***

As shown in Figure 4, field-level data captured by IoT sensors and drones is transmitted to cloud or edge computing platforms, where AI analytics engines convert raw data into recommendations delivered to the farmer through a decision-support interface. The farmer's resulting actions complete the feedback loop by altering field conditions, which are then re-sensed in the next cycle.

## V. DISCUSSION

The results indicate that Indian digital agriculture adoption follows a consistent pattern: technologies addressing acute, highly visible constraints have achieved the broadest practical reach, while capital-intensive technologies remain concentrated among commercial operations. Smart irrigation and IoT sensing, which directly target water scarcity, have produced the most concretely documented outcomes, with field studies reporting 20-35% water savings alongside 10-20% yield improvements. Similarly, AI-based advisory tools have achieved substantial reach precisely because they are low-cost and delivered through smartphones already owned by most farmers, as reflected in the tens of millions of queries handled by multilingual chatbot platforms.

By contrast, robotics, precision-agriculture equipment, and blockchain-based traceability systems remain comparatively nascent in smallholder contexts, reflecting their higher capital requirements and dependence on reliable digital and physical infrastructure. This suggests that near-term digitalization strategy in India should prioritize sharedservice and custom-hiring models for capital-intensive technologies, while continuing to scale the low-cost sensing and AI-advisory tools that have already demonstrated measurable field-level impact.

These findings matter because India's agricultural sector is structurally dominated by smallholders, meaning that technology strategies optimized for large commercial farms elsewhere may not transfer directly. The comparative evidence assembled here suggests that affordability and infrastructure-independence, rather than technical sophistication alone, are the primary determinants of successful adoption in the Indian context.

Several limitations of this review should be acknowledged. First, this is a concise, non-systematic overview rather than an exhaustive systematic review, and it does not apply formal quality-appraisal scoring to included sources. Second, the evidence base for India-specific field outcomes remains uneven across technology domains: while smart irrigation and IoT sensing have relatively well-documented field trial results, technologies such as blockchain and Agriculture 5.0 are represented primarily by conceptual or early-stage studies rather than large-scale field validation. Third, because the review draws on secondary published sources rather than primary data collection, it cannot independently verify the generalizability of reported outcomes beyond the specific sites and conditions described in the original studies.

In summary, digital technologies are measurably reshaping Indian agriculture, but their benefits are not yet distributed evenly across the technology landscape or the farmer population. Continued, coordinated investment in rural digital infrastructure, farmer training, and locally adapted, affordable technology design will be necessary to extend these benefits more equitably across India's smallholder-dominated agricultural sector.

## VI. FUTURE SCOPE

Building on the findings above, several emerging directions are likely to shape the next phase of India's agricultural digitalization. Edge AI, which deploys compact, quantized models directly on low-cost field hardware, is expected to reduce dependence on continuous rural connectivity, enabling disease detection and irrigation control to continue functioning during network outages [19].

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Digital twins, which maintain continuously updated virtual replicas of individual farms or fields, offer the prospect of simulation-based decision support, allowing farmers and advisors to test irrigation or fertilization strategies virtually before field implementation; Indian deployments of this kind nonetheless remain largely at the pilot stage [20].

Explainable AI techniques, which render model recommendations interpretable to non-expert users, are increasingly recognized as necessary for building farmer trust in AI-driven advisory systems, particularly given the financial and agronomic stakes of crop-management decisions [21].

Autonomous farming, integrating robotics, computer vision, and AI decision-making with minimal human intervention, is progressing rapidly in commercial-scale operations and is likely to reach Indian custom-hiring service centers before individual smallholders, given current capital cost structures [22].

Finally, sustainability considerations, including water conservation, reduced agrochemical use, and climate-resilient crop planning, are increasingly embedded as explicit design objectives within digital agriculture platforms, consistent with the human-centric and agroecological principles articulated under the emerging Agriculture 5.0 paradigm. Taken together, these directions suggest that the next phase of Indian agricultural digitalization will be defined not only by continued technical advancement but by the extent to which these technologies can be made affordable, interpretable, and accessible to the smallholder farmers who form the backbone of the sector.

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