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FROM TRACEABILITY TO PREDICTIVE INTELLIGENCE: A SYSTEMATIC-NARRATIVE REVIEW OF IOT, BLOCKCHAIN, AND AI IN AGRICULTURE

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ABSTRACT

The convergence of Internet of Things (IoT), blockchain, and artificial intelligence (AI) has emerged as a transformative force in advancing sustainable agriculture. These technologies collectively address persistent challenges in traceability, resource optimization, data security, and decision support. This review conducts a systematic-narrative analysis of journal publications from 2020 to 2025, synthesizing insights across three thematic dimensions: (i) IoT-Blockchain frameworks for agricultural supply chain traceability, (ii) IoT-AI/ML approaches for predictive farming and crop health monitoring, and (iii) blockchain-driven data management for breeding and genomic applications. Across the themes, the reviewed studies demonstrate substantial improvements, including enhanced supply chain transparency, predictive accuracy exceeding 95% in crop disease classification, and scalable storage architectures for high-throughput breeding data. However, challenges persist in interoperability, scalability, energy efficiency, and end-user adoption. The review identifies critical research gaps and emphasizes the need for integrated frameworks that balance technological sophistication with practical usability. By consolidating current advances and limitations, this study provides a comprehensive understanding of the evolving IoT-Blockchain-AI ecosystem in agriculture and outlines future directions toward sustainable, transparent, and intelligent agri-food systems.



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I. INTRODUCTION

Global agriculture faces mounting challenges: fragmented and opaque supply chains, frequent food-safety incidents, inefficient resource use, and rapidly growing volumes of farm and genomic data that require trustworthy, scalable management. Digital traceability remains incomplete across many value chains, hampering rapid recall decisions and eroding consumer trust; simultaneous pressures to improve sustainability and reduce post-harvest loss increase the urgency for technological solutions [1], [2]. The Internet of Things (IoT) brings dense, low-cost sensing and near-real-time telemetry to the farm and supply chain: soil moisture, temperature, cold-chain conditions, geolocation, and spectral or image data can now be captured continuously [3]. IoT enables precision interventions for irrigation, fertilization, pest control and produces the high-resolution provenance streams needed for verifiable analytics. However, IoT data by itself cannot guarantee immutability, distributed trust, or automated contractual enforcement across multiple stakeholders [4].

Blockchain (BC) offers complementary properties — a tamper-evident ledger, decentralized trust, and programmable smart contracts — which can help secure IoT data, automate transactions, and provide auditable provenance from farm to fork. Yet practical deployment raises important questions about cost, scalability, and the resource constraints of low-power IoT devices; careful architectural design and hybrid solutions such as edge gateways, private chains, data-hashing strategies are frequently proposed to balance trust and efficiency [5]. Several recent literature reviews and systematic studies have examined blockchain and occasionally IoT applications in agri-food systems, identifying common benefits (traceability, transparency, fraud reduction) and recurring barriers (interoperability, legal/regulatory concerns, adoption costs). For instance, by [6] analyzed adoption barriers and enablers for blockchain in smart and sustainable agriculture; in [7] systematically reviewed blockchain applications across food supply chains and identified under-utilized drivers and research gaps; by [8] assessed blockchain and IoT technologies in the context of regional feasibility and implementation constraints. These reviews are valuable but either focus narrowly on adoption drivers, concentrate mainly on supply-chain aspects, or synthesize literature that predates the recent surge (2020–2025) of IoT + blockchain empirical work.

I.1 CONTRIBUTIONS OF THIS REVIEW

This article addresses the above gaps by conducting a systematic–narrative review of journal publications from 2020 to 2025, with the following contributions:

- **Comprehensive scope:** covers 30 peer-reviewed journal articles on IoT–blockchain integration in agriculture.
- **Structured thematic analysis:** classifies studies into four themes: (1) Supply-chain traceability and provenance, (2) Smart/precision agriculture, and (3) Crop-breeding and genomic data management.
- **Critical synthesis:** compares methodological choices such as blockchain architectures (public, private, hybrid), on-chain/off-chain data strategies, and edge integration with IoT.
- **Identification of gaps:** highlights unresolved issues including scalability, energy costs, interoperability, and regulatory alignment.
- **Future research agenda:** proposes directions such as energy-efficient consensus mechanisms, cross-chain interoperability, and integration of genomic and AI-driven farming solutions.

II. METHODS

II.1 REVIEW TYPE

This work adopts a systematic–narrative review approach. The systematic component ensures transparent and reproducible identification of relevant literature, while the narrative synthesis allows for flexible integration of diverse study designs, applications, and technological perspectives. This combination is particularly suitable given the multidisciplinary nature of IoT–blockchain applications in agriculture, spanning supply chain traceability, precision farming, genomic data management, and adoption studies.

II.2 SEARCH STRATEGY

A structured literature search was conducted across major academic databases, including Scopus, Web of Science, IEEE Xplore, ScienceDirect, SpringerLink, Wiley Online Library, MDPI, and Taylor & Francis Online. The search covered the period from 2020 to August 2025 and was limited to publications in English. Boolean search strings were employed to capture relevant studies, such as:

- “IoT” AND “Blockchain” AND “Agriculture”
- “Smart farming” AND “Blockchain”
- “Blockchain” AND “Food supply chain” AND “IoT”
- “Blockchain” AND “Genomic data” AND “Agriculture”

These combinations were iteratively refined to maximize coverage across agricultural domains where IoT and blockchain intersect.

II.3 INCLUSION AND EXCLUSION CRITERIA

Studies were included if they:

- Were peer-reviewed journal articles.
- Reported original research (empirical, applied, or technical).
- Explicitly integrated IoT and blockchain technologies in agricultural contexts.

Studies were excluded if they:

- Were conference proceedings, book chapters, or review papers.
- Focused exclusively on blockchain or IoT without integration.
- Presented purely conceptual frameworks with no implementation or application.

II.4 SELECTION PROCESS

The initial search retrieved a large pool of records. After deduplication, titles and abstracts were screened for relevance. Full-text evaluation was then performed to assess eligibility against the defined criteria. At the end of this process, 30 journal articles were retained for analysis.

II.5 DATA EXTRACTION AND THEMATIC GROUPING

For each included article, key bibliographic and methodological details were extracted, including publication year, application domain, blockchain architecture, IoT scope, and study contribution. The articles were then organized into three thematic categories reflecting their primary focus:

1. Supply chain traceability and provenance.
2. Smart and precision agriculture.
3. Crop breeding and genomic data management.

This thematic grouping enables cross-comparison of methodological approaches, application domains, and identified research gaps.

II.6 PRISMA DIAGRAM

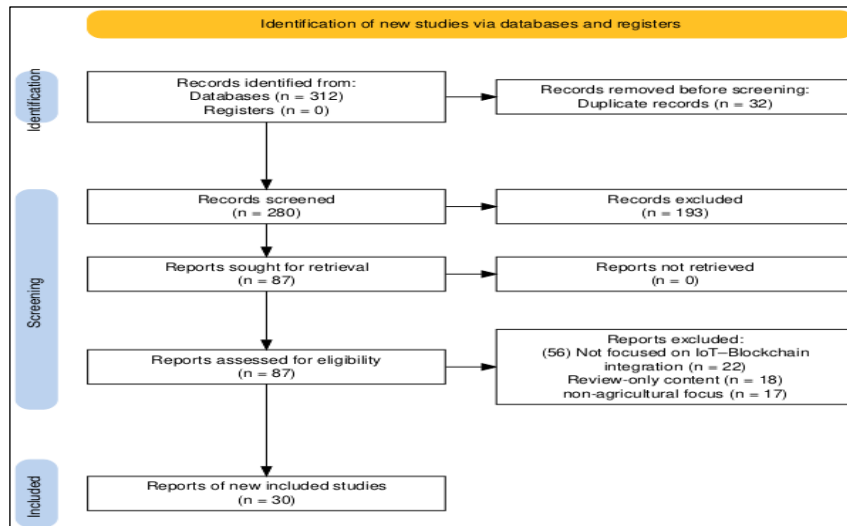


Figure 1: PRISMA flow diagram of study selection process.

Source: Authors, (2026).

Figure 1 shows the selection process of the studies included in this review. A total of 312 records were initially identified through database searches. After removal of 32 duplicates, 280 records remained for screening. Following title and abstract evaluation, 193 records were excluded for irrelevance. The full texts of 87 reports were then assessed for eligibility, of which 56 were excluded due to reasons such as lack of IoT-Blockchain integration (22), review-only content (18), or non-agricultural focus (17). Finally, 30 studies fulfilled the inclusion criteria and were retained for detailed synthesis.

III. RESULTS

III.1 THEME 1: SUPPLY CHAIN TRACEABILITY AND PROVENANCE

Traceability research moved quickly from proof-of-concept immutable ledgers to systems that must also solve privacy, latency, storage growth, data trustworthiness, and operational usefulness.

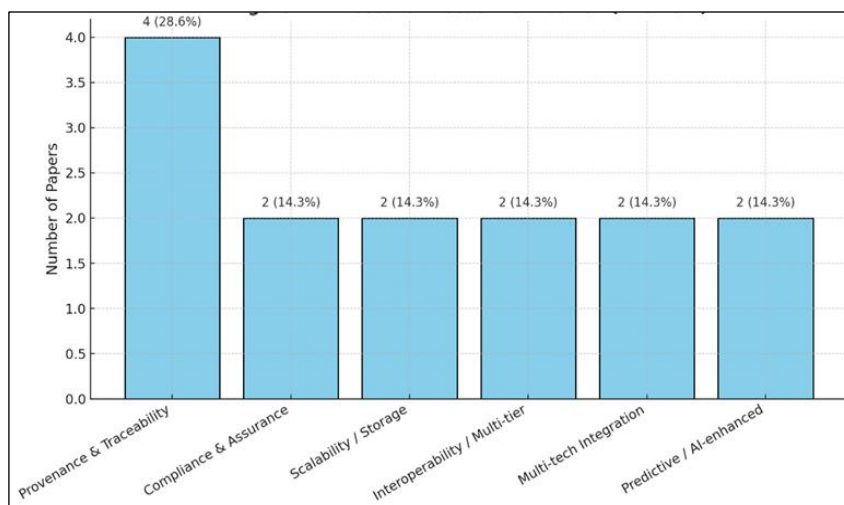


Figure 2: Research focus distribution on theme 1.

Source: Authors, (2026).

Figure 2 shows the research focus distribution of Theme 1 papers on IoT–Blockchain for agricultural product traceability. Most studies focus on provenance and privacy (3 papers), followed by compliance frameworks (2), scalability solutions (2), interoperability designs (2), multi-technology integration (2), and predictive/AI methods (2). Provenance is the dominant focus, while interoperability and prediction remain less explored. The following paragraphs synthesize how key papers address these problems, comparing what each did to what the others missed or improved.

III.1.1 On-Chain Vs Hybrid Storage and The Price of Verifiability

According to [9] established an influential hybrid pattern — store a compact Merkle root on Ethereum and put bulky provenance files in IPFS — using SHA-256 and Merkle trees to keep integrity while limiting on-chain data. Their measured numbers (per-function gas $\approx$ USD 0.29–0.45; SHA-256 $\sim$ 2 s for 1 GB; IPFS upload 243 MB $\approx$ 3.4 s, query $\approx$ 22 s) make explicit the trade-off: verifiable provenance is feasible but public-chain gas costs quickly become a bottleneck. In [10] respond to this by moving to permissioned PoA Ethereum (IoT-GChain): they keep the hybrid storage model (IPFS + on-chain hash) but change consensus to PoA, yielding block times $\approx$ 3 s and gas per operation in the 85k–134k units range. In short, [9] proves the hybrid technique; [10] demonstrates how consensus choice changes latency and practical viability.

III.1.2 Privacy, Compliance and Contract Logic

Where [9] prioritized privacy by minimizing on-chain payloads, by [11] encoded compliance rules directly into contracts via the Trust-Enhanced Contract Algorithm (TECA). TECA performs multi-party validation (sensor verification + certification rules) BEFORE a claim is anchored, thereby reducing on-chain noise and ensuring only verified claims are recorded. According to [11] BSAA reports gas 41k–102k units, $\sim$ USD 0.25 average transaction cost and 18–20 TPS — a clear demonstration that smart contract logic + careful write policies can permit practical throughput for assurance workflows, unlike naive full-data writes on public chains.

III.1.3 Integrating Analytics and Operational Value

According to [12] integrate forecasting directly with provenance: a GA-tuned ensemble (LSTM + GRU) reduces RMSE from 872.6 / 819.7 to 512.2, while provenance sits on a permissioned blockchain with Hyperledger Caliper tests showing median latencies $\sim$ 198–768 ms for 200–800 nodes. Contrast this with by [13], who do not aim at RNN forecasting but show that classical ML applied to RFID/WSN transport data gives immediate operational value — RF 95.5%, AdaBoost 94.3%, SVM 91.7%, KNN 89.6% — yet [13] Bhutta do not evaluate blockchain latency/cost. Thus: [10]–11 shows deep-learning + private chain is feasible (in sim), [13] shows classical ML yields very high accuracy in transport forecasting but leaves blockchain operational costs unexplored. Combining both approaches would be a logical next step.

III.1.4 Scalability and Storage Lifecycle (redaction & parallelism)

Canonical append-only ledgers cause storage bloat; by [14] propose redactable primitives (chameleon hash) + parallel chain architecture + CP-ABE and report $\sim$ 52.38% reduction in storage footprint over 360k wheat records. Compare that with AgriChainSync [15], which employs a Dynamic Storage Algorithm (DSA) and a Feedback & Adaptation Module (FAM): under experimental load (100–1000 IoT devices) [15] AgriChainSync shows latency increase $\approx$ 15% under $10\times$ data volume and improved storage efficiency. LAP-chain [14] solves data retention/compliance explicitly (delete or redact expired data); [15] AgriChainSync emphasizes adaptive routing to balance cost vs latency. Both demonstrate that architecture + algorithms can control storage growth — a capability absent from many early single-chain designs [9],[16].

III.1.5 Data-Quality at Capture: Sensor Fusion, NIRS And Multi-Tech Verification

According to [17], [18] highlight an often-ignored truth: immutability cannot fix bad inputs. [17] integrates NIRS + RFID + IoT to verify quality signals before anchoring; Paper [18] implements embedded IoT + permissioned chain in an industrial hemp deployment. These works contrast with Papers [9–12] and show that adding certified sensing (NIRS, RFID) is required to make an immutable chain trustworthy for quality claims. Practically, this means systems should include sensor-level verification algorithms as pre-contract checks — a capability shown in Papers [17], [18] but missing in many ledger-centric designs.

III.1.6 Interoperability, Governance and End-To-End Integration

In [19] propose a vertical-chains + core hash-chain model for stakeholder privacy and scalability; by [16] provide an end-to-end Ethereum + IPFS stack with a reputation subsystem, but both lack large-scale field results. According to [20] push for end-to-end visibility (edge gateways $\rightarrow$ chain), yet they report little performance detail. Thus the field is converging on multi-chain / core-chain topologies + governance policies as necessary for multi-stakeholder adoption, but real-world interoperability experiments are still scarce.

Table 1: Summary of theme 1.

Paper	Methods / Architecture	Algorithms / Techniques	Key Results / Performance	Limitations / Challenges
[12]. Khan et al. (2020)	Private blockchain + IoT + predictive analytics	GA-optimized ensemble of LSTM + GRU	RMSE reduced to 512.2 vs. 872.6 (LSTM) & 819.7 (GRU); query latency 198–768 ms over 200–800 nodes	Tested only in simulated private networks
[20] El Mane et al. (2024)	End-to-end IoT–Blockchain architecture (8-node network)	Controllers/validators added dynamically	Latency margin $\approx$ 100–120s; throughput $\approx$ 235–260 TPS on 3.5 GHz CPU, 32 GB	Latency rises with heavy concurrent traffic; no energy cost evaluation

			RAM; improved performance with more validators	
[21]. Guo et al. (2025)	Hyperledger Fabric + IoT sensors + smart contracts	Blockchain-based trusted traceability	File transfer: upload ≈ 7.31 MB/s (small), 15.19 MB/s (large); download ≈ 31.92 MB/s (small), 35.61 MB/s (large) $\rightarrow$ meets real-time traceability needs	Mostly tested on grape supply chain; lacks broader validation
[19]. Bhat et al. (2022)	Agri-SCM-BioT: vertical blockchains + core chain	Controlled access via master/gateway nodes	Secure master nodes reduce 51% attack risks; high-resource nodes improve resilience	No reported values for latency, storage cost, or throughput
[15]. Tahir et al. (2024)	AgriChainSync (hybrid IoT-AI-Blockchain)	Dynamic storage + homomorphic encryption	Latency increase only 15% under $10\times$ data load; throughput robust; storage efficiency improved	Energy/operational overhead not deeply analyzed
[16]. Shahid et al. (2020)	Ethereum + IPFS for provenance, trading, reputation	Multiple smart contracts	Simulation: gas usage scales with products; improved transparency and auditability	Cost/latency not quantified in USD terms

Source: Authors, (2026).

Progress is evident in: (a) hybrid storage patterns (Merkle root + IPFS), (b) permissioned consensus (PoA/Hyperledger) to lower latency and fees, (c) integration of analytics for operational decision support, and (d) architectural work to tackle storage retention (redactable/parallel chains) and interoperability (multi-chain). Remaining bottlenecks are consistent across studies: lack of large-scale field validations, incomplete cross-paper reporting of latency/cost metrics in a unified format, and few integrated demonstrations that combine sensor verification, optimized contract logic (TECA/DSA), and analytics (RNN/RF) in a single production deployment. Table 1 provides a comparative summary of some studies highlighting their methods, algorithms, key results, and limitations.

III.2 THEME 2: SMART AND PRECISION AGRICULTURE

Research at the intersection of IoT and blockchain in agriculture has evolved toward secure, privacy-preserving, and energy-efficient systems that also support predictive intelligence and supply chain transparency. The eleven papers reviewed under this theme (22–32) demonstrate different approaches to address challenges such as security and trust, prediction accuracy and anomaly detection, privacy-preserving collaborative learning, IoT network efficiency, and supply chain sustainability. Figure 3 shows the distribution of research focus in IoT + Blockchain for Smart and Precision Agriculture based on 11 reviewed papers. The largest focus is on Security & Trust (27%) and Network/Energy Efficiency (27%), followed by Prediction & ML (18%), Supply Chain Transparency (18%), and Privacy & Federated Learning (9%). This highlights key research priorities and gaps in the field.

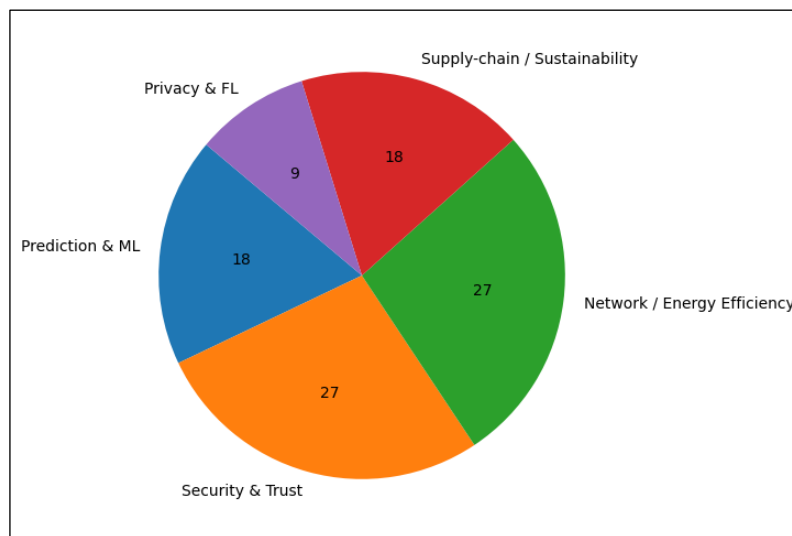


Figure 3: Research focus distribution on theme 2.

Source: Authors, (2026).

III.2.1 Security and Data Integrity

Maintaining trustworthy and tamper-resistant agricultural data is a fundamental requirement. According to [22] combined edge devices (ESP32, Arduino) with AWS IoT and Ethereum testnet smart contracts, achieving average alarm response latency of ≈ 0.11 seconds, demonstrating the feasibility of automated IoT–blockchain alarms. Similarly, by [23] proposed a cloud-enabled security monitoring system where IoT sensor data is processed in AWS Lambda and anchored to blockchain, reporting IoT-to-cloud latency of ≈ 2 s, Ethereum confirmation ≈ 7 s, and full end-to-end alerts within ≈ 9 s. According to [24] focused on blockchain cost-efficiency, analyzing smart contract gas usage, where typical IoT checks consumed $\approx 29,217$ gas units, highlighting the economic trade-off between security automation and blockchain overhead. Together, these works confirm that edge-assisted detection with blockchain anchoring ensures trustworthy event logging, though scalability to production systems demands gas optimization or migration to permissioned/Layer-2 chains.

III.2.2 Prediction Accuracy and Anomaly Detection

Several studies demonstrate the potential of combining IoT data with blockchain-backed integrity guarantees for accurate prediction and anomaly detection. For [25] used a binary Slime Mould Algorithm (SMA) for feature selection with Bi-LSTM and GRU models, achieving yield prediction accuracy $\approx 95.8\%$, F1 scores ≈ 0.96 , and anomaly detection precision of ≈ 0.93 , while ensuring nearly 100% integrity via blockchain. According to [26] employed classical ML approaches for crop recommendation, achieving accuracies up to 98.2%, showing that interpretable models can perform strongly in structured IoT datasets. In [27] applied CNN-LSTM hybrids under federated learning, where centralized models reached RMSE ≈ 4.70 and $R^2 \approx 0.84$, while privacy-preserving FL variants showed slightly degraded RMSE ≈ 5.15 – 5.90 . According to [28] proposed Smart-Agri, an IoT–ML–Blockchain framework, achieving $\approx 89.5\%$ accuracy in crop monitoring and control. These results indicate that DL consistently provides superior predictive performance, though classical ML remains competitive when computation must remain lightweight.

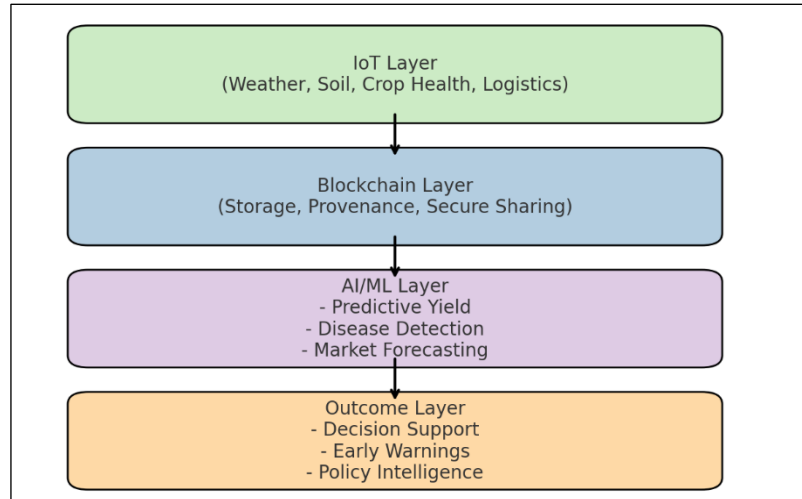


Figure 4: Pipeline of IoT, Blockchain, and AI integration for predictive agricultural insights.

Source: Authors, (2026).

This framework illustrates (Figure 4) how IoT devices capture real-time agricultural data, which is securely managed through blockchain before being processed by AI/ML models for predictive insights. The outcome enables decision support, early warnings, and policy-level intelligence.

III.2.3 Privacy-Preserving Collaborative Learning

Sharing agricultural data across stakeholders raises privacy risks, which several works addressed by integrating federated learning (FL) with blockchain provenance. The federated architecture of by [27] demonstrated that CNN-LSTM models can be trained collaboratively without exposing raw farm data. Differential privacy extensions further strengthened protection but increased RMSE to ≈ 5.90 compared to ≈ 4.70 in centralized training. While latency and blockchain throughput were reported as “acceptable,” detailed network stress tests remain scarce. These findings confirm that federated learning with blockchain is a viable solution for multi-party collaboration, but future work must optimize trade-offs between privacy guarantees and predictive accuracy.

III.2.4 IoT Network Efficiency, Energy, and Mobility

The reliability and sustainability of IoT sensor networks in agriculture are critical for real-world deployments. In [29] proposed an energy-aware clustering protocol, achieving substantial improvements compared to the LEACH baseline: network lifetime extended by +112%, stability period increased by +23%, and energy consumption reduced by –68%. According to [30] examined precision agriculture networks with 6LoWPAN and RPL routing under both fixed and mobile topologies. Results showed that fixed nodes achieved stable connectivity and lower radio duty cycles, while mobility increased energy costs and connectivity fluctuations, though precise percentages were less detailed. Collectively, these studies demonstrate that energy-efficient clustering significantly extends sensor lifetimes, while robust routing protocols remain an open challenge for mobile agricultural IoT environments.

III.2.5 Supply Chain Transparency and Sustainability

Ensuring end-to-end transparency from farm to consumer remains a central objective. In [31] proposed a semantic cyber–physical system (CPS) that integrates IoT, blockchain, AI, and remote sensing for traceability, reporting improved decision support and qualitative gains in transparency, though without quantitative latency or cost metrics. According to [32] applied TOPSIS-based multi-criteria analysis to identify and rank barriers to blockchain adoption in green agricultural supply chains, emphasizing issues such as regulatory compliance and trust. According to [24] further demonstrated how blockchain smart contracts can automate supply chain agreements, reporting explicit transaction costs across agricultural IoT scenarios. Collectively, these works highlight that semantic architectures and multi-criteria frameworks provide conceptual clarity, but cost-efficient blockchain execution remains the most urgent bottleneck for real-world adoption.

Table 2 highlights the core contributions of each work in terms of architecture, algorithms, and outcomes, showing how researchers have leveraged blockchain to ensure confidentiality, integrity, and secure sharing of agricultural IoT data.

Table 2: Comparative summary of Theme 2 papers.

Paper (no.)	Methods & architecture	Algorithms / techniques	Key results
[22] Aliyu & Liu (2023)	ESP32 IoT nodes → AWS cloud (IoT Core + Lambda) → Ethereum (Rinkeby); smart contracts automate responses	Edge threshold/rule detection; Solidity smart contracts; on-chain logging	Observed transaction counts ≈ 109k–291k avg network latency ≈ 0.11 s
[29] Wang et al. (2025)	Human-Cyber-Physical System combining IoT, remote sensing, AI, semantic blockchain layer	Semantic data integration; H-CPS architecture (conceptual)	Qualitative improvements in traceability and cost-efficiency reported
[25] Almazmomi (2025)	4-layer framework: data acquisition, AI layer, security layer, blockchain layer	Binary SMA for feature selection; Bi-LSTM, GRU for prediction; blockchain for integrity	Yield accuracy: 95.8% (Bi-LSTM) 94.6% (GRU); F1 ≈ 0.96/0.94; anomaly detection precision 0.93, recall 0.92; blockchain integrity ↑ ≈97%
[28] Hossain et al. (2023)	IoT sensors + cloud + mobile UI + blockchain for integrity; energy harvesting for sensors	ML recommendation model (unspecified) for irrigation/fertilizer; blockchain for logging	ML model accuracy ≈ 89.5% in their experiments; system supports remote control and energy harvesting
[30] Atalla et al. (2023)	WSN simulation (COOJA) with 6LoWPAN + RPL; scenarios: fixed-node (olive farm) and mobile nodes (stable)	RPL routing; Random Waypoint mobility model; COOJA simulation	Fixed-node: more stable connectivity and lower power consumption; mobile-node: higher radio duty cycle and connectivity fluctuation
[27] Manoj et al. (2025)	Federated learning orchestration + blockchain ledger (DIDs, VCs) for authentication & provenance	CNN-LSTM, ResNet-16/28, CNN-DNN as models; DP-FL variants; smart contracts for metadata logging	Centralized CNN-LSTM: MSE ≈ 22.07, RMSE ≈ 4.70, R ² ≈ 0.84 (2018); DP-FL (3 clients IID): MSE ≈ 26.50, RMSE ≈ 5.15, R ² ≈ 0.77;
[31] Awan et al. (2021)	3-layer IoT architecture with clustering protocol + blockchain logging	Custom energy-efficient clustering protocol (LEACH-variant)	Compared to LEACH: +23% network stability, −68% energy consumption, +112% network lifetime
[32] Chaudhari et al. (2025)	IoT data collection + blockchain for secure tracking; TOPSIS for barrier prioritization	TOPSIS multi-criteria decision method; IoT + blockchain architecture for GSCM	Ranked adoption barriers and proposed prioritized interventions
[23] Chaganti et al. (2022)	Arduino/ESP8266 sensors → AWS IoT Core + Lambda → Ethereum (Rinkeby) via Infura; Web3 UI	Threshold-based anomaly detection in Lambda; Solidity smart contracts for logging	IoT→cloud publish ≈ 2 s; Ethereum tx ≈ 7 s; end-to-end alert ≈ 9s
[26] Bakthavatchalam et al. (2022)	IoT sensors measuring N,P,K,pH,temp,humidity,rainfall; dataset (2,200 instances)	MLP, Jrip, Decision Table classifiers (WEKA)	MLP accuracy ≈ 98.23%, Jrip ≈ 96.23%, Decision Table ≈ 88.59%; ROC ≈ 0.991–0.997; model build times 0.15–10.56 s
[24] Pranto et al. (2021)	IoT sensors + Solidity smart contracts on Ethereum testbed; MQTT messaging; contract functions for storage/distribution	Solidity smart contracts (self-check/trigger functions), off-chain sensor input via MQTT	Gas usage per operation addSeed() transaction 168,402 gas (transaction) / 144,314 (execution); temperatureSelfCheck() 50,681 / 29,217 gas; retailSell() 91,464 / 69,808 gas

Source: Authors, (2026).

Overall, the reviewed studies show clear trends: (i) edge-assisted smart contracts can deliver real-time security but gas costs demand optimization; (ii) deep learning approaches achieve high prediction accuracy, while federated learning enables privacy-preserving collaboration at modest performance trade-offs; (iii) energy-aware clustering yields measurable IoT lifetime extensions, making it one of the most deployment-ready innovations; and (iv) semantic frameworks and barrier analyses advance conceptual supply chain trust, though empirical cost and latency data are still underreported.

The comparative evidence suggests that privacy-preserving deep learning and energy-optimized IoT protocols, tightly integrated with blockchain provenance, represent the most promising direction for next-generation precision agriculture ecosystems.

III.3 THEME 3: CROP BREEDING, GENOMICS & DATA MANAGEMENT

Theme 3 papers focus on the integration of blockchain, IoT, and advanced computational methods (ML, encryption, privacy-preserving frameworks) to address the growing challenges in crop breeding, genomics, and large-scale agricultural data management. The reviewed studies contribute solutions for high-throughput data storage, secure genomic management, breeding efficiency, and supply chain traceability, while also revealing gaps related to scalability, security-performance trade-offs, and integration of advanced analytics. Figure 5 demonstrates the role of IoT in collecting genomic and field data, with blockchain ensuring secure storage, provenance, and controlled sharing. This integration strengthens breeding programs, genomic research, and collaborative data management.

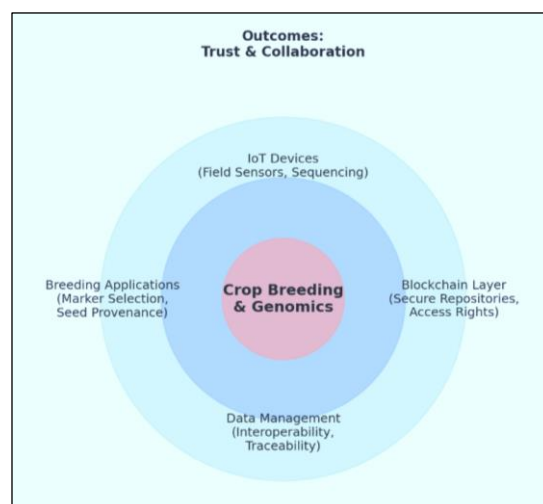


Figure 5: Framework of IoT and Blockchain in crop breeding, genomics, and data management.

Source: Authors, (2026).

III.3.1 Data Storage, Compression & Retrieval

According to [33] developed a spectral data pipeline within Breedbase, demonstrating 40% compression via differential computation and 50% faster retrieval with indexing, while PCA captured >85% variance for dimensionality reduction. However, robust blockchain-level security was absent. In contrast, [34] implemented multi-chain blockchain architecture with proxy encryption for GSBCP, which significantly improved system concurrency and secure storage of sensitive breeding data. Both works show how storage and retrieval challenges are addressed, but [33] emphasized efficiency while by [34] focused on security-performance trade-offs.

III.3.1.1 Breeding Information Management & Genealogy Tracking

According to [35] proposed a Hybrid Crop Breeding Information Management System (HCBIMS) with diallel crossing design, GCA/SCA analysis, and genealogy tracking, doubling efficiency in combining ability test analyses. This was further supported by compound genealogy tools, which enhanced lineage tracking. Similarly, [36] built a relational database-based breeding trait tracking system, enabling faster querying and visualization, with higher data accuracy than manual methods. While both improved breeder decision-making, neither incorporated blockchain security.

III.3.1.2 Secure Genomics & Privacy Preservation

According to [37] introduced a blockchain-based privacy-preserving genomic data system with Local Differential Privacy (LDP). It separated encrypted private storage for staff and irreversibly modified semi-private storage for external access, ensuring confidentiality, access control, and user monitoring. However, the study lacked ML-driven analytics for predictive genomics. Compared to [34], which emphasized proxy encryption and multi-chain performance, Park's contribution primarily addressed privacy and fine-grained access control.

III.3.1.3 Supply Chain Traceability & End-to-End Data Integrity

According to [38] extended blockchain applications beyond breeding to food grain traceability. By combining IoT sensors (temperature, humidity, GPS) with Ethereum blockchain, IPFS, and ML algorithms, the system enhanced scalability, throughput, and latency. Notably, it maintained strong confidentiality, integrity, availability, and non-repudiation guarantees. Unlike in [33], [35] works that focused on breeding data management, by [38] contribution highlighted how blockchain-IoT-ML convergence can secure the entire crop supply chain lifecycle. Table 3 presents a comparative overview of Theme 3 papers, highlighting their methods, algorithms, achieved results, and the specific agricultural challenges they addressed.

Table 3: Comparative summary of theme 3.

Paper	Methods / Techniques	Results / Performance	Challenges Addressed
Hershberger et al. (2021) [33]	Breedbase pipeline, differential compression, PCA	40% compression, 50% faster queries, >85% variance retained	Storage efficiency, retrieval speed
[34] Zhang et al. (2020)	Multi-chain blockchain, proxy encryption, GSBCP	Improved concurrency, secure storage with layered access	Data security, storage scalability
Han et al. (2020) [35]	HCBIMS, diallel crossing, GCA/SCA analysis, genealogy tool	Doubled efficiency in combining ability analysis, automated reports	Breeding efficiency, lineage tracking
Basheija et al. (2021) [36]	Relational DB, phenotype trait tracking, custom algorithm	Faster querying, higher accuracy than manual methods	Data organization, real-time decision support
[37] Park et al. (2021)	Blockchain + LDP, dual storage (private/semi-private)	Privacy-preserving genomic access control, staff & external data segregation	Data privacy, access monitoring
[38] Agarwal et al. (2024)	IoT sensors, Ethereum, IPFS, ML anomaly detection	High throughput, low latency, strong CIA+NR security	Transparency, anomaly detection, supply chain scalability

Source: Authors, (2026).

In synthesis, Theme 3 highlights how the triad of IoT, blockchain, and ML is not just an incremental enhancement of existing agricultural systems but rather a paradigm shift toward intelligent, decentralized, and resilient agri-ecosystems. The works reveal a trajectory where trust (blockchain), perception (IoT), and cognition (ML) are interwoven, pointing to a future in which agricultural decision-making is secure, explainable, and adaptive to uncertainties—a cornerstone for next-generation digital agriculture.

IV. CHALLENGES & FUTURE DIRECTIONS

- ✓ A major research gap lies in the integration of heterogeneous agricultural data sources, where IoT sensor streams, spectral datasets, blockchain transaction records, and genomic information remain fragmented, limiting holistic insights.
- ✓ Scalability challenges persist as most proposed systems have been validated on limited datasets or small-scale pilots, restricting their applicability to high-throughput crop breeding pipelines or multi-stakeholder agricultural supply chains.
- ✓ Interoperability issues continue to hinder progress, with the absence of standardized frameworks preventing seamless cross-platform data exchange between IoT–Blockchain–ML ecosystems and breeding information systems.
- ✓ Security and privacy concerns remain inadequately addressed, particularly for sensitive genomic and phenotypic data, where existing blockchain mechanisms ensure transparency but fail to provide fine-grained confidentiality.
- ✓ User-centric limitations emerge as farmer usability, cost-effective deployment, and real-time decision support features are often overlooked, reducing the practical adoption of these advanced technologies in resource-constrained environments.
- ✓ Energy and cost constraints are evident, as blockchain and IoT-driven solutions demand significant computational and communication resources, posing barriers for sustainable agricultural implementation.

❖ Future directions

- ✓ Future directions point towards the deployment of federated and edge AI frameworks that enable scalable, privacy-preserving analytics without centralized data pooling.
- ✓ Hybrid blockchain models that integrate lightweight consensus mechanisms with sharding are needed to balance transparency, efficiency, and real-world feasibility in agricultural contexts.
- ✓ The development of interoperable standards for multi-source agricultural data exchange will be critical in bridging the gap between phenotyping, breeding, and supply chain systems.
- ✓ The incorporation of explainable AI and XAI frameworks is essential to ensure interpretability and trust in decision support for breeding, disease detection, and traceability tasks.
- ✓ Sustainable computing paradigms, including green blockchain and energy-efficient IoT deployments, are required to mitigate the environmental and economic costs of digital agriculture.
- ✓ Farmer-centric innovations such as mobile-based decision support, fuzzy reasoning mechanisms, and multilingual interfaces will play a vital role in democratizing access to advanced IoT–Blockchain–ML solutions in agriculture.

V. CONCLUSIONS

This review critically analyzed the integration of IoT, blockchain, and AI/ML technologies across three thematic dimensions: agricultural supply chain traceability, smart farming with predictive intelligence, and breeding/genomic data management. The findings highlight that blockchain ensures transparency, immutability, and trust, IoT enables real-time monitoring of agricultural processes, and AI/ML enhances predictive accuracy and intelligent decision-making. In Theme 1, blockchain–IoT frameworks improved traceability and security across food supply chains, though issues of interoperability and scalability remain unresolved. Theme 2 emphasized predictive modeling for crop health and resource optimization, where hybrid deep learning models such as CNN-LSTM and Bi-LSTM achieved high accuracy (up to 96%) and improved efficiency, yet challenges of energy consumption and cost persist. Theme 3 demonstrated blockchain's role in securely managing high-throughput breeding and genomic data, supported by lightweight architectures and proxy encryption, though concerns around system sustainability and farmer usability continue.

Overall, while significant progress has been made, critical gaps remain in scalability, standardization, and user-centric design. Future research must focus on interoperable, explainable, and sustainable frameworks that combine technological robustness with accessibility for diverse stakeholders. Addressing these gaps will enable IoT–Blockchain–AI ecosystems to evolve into a resilient foundation for next-generation smart agriculture.

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