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Mapping IoT performance across agri-food supply chain stages: A dual-method evidence synthesis

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Abstract

Internet of Things research in agri-food supply chains has expanded rapidly, but evidence of operational performance remains uneven across stages. We combined bibliometric mapping of 625 records (2015–2025) with a PRISMA 2020 systematic review and JBI appraisal of 68 studies covering seven stages. Production provided the strongest evidence: one two-year soybean trial reported 23.1–29.1% higher yield under precision irrigation than under flood irrigation. Storage and transportation offered moderate observational evidence of improved temperature-excursion detection and response, whereas evidence remained limited in the distribution-and-retail and consumption stages. The review separates publication activity from demonstrated performance, quantifies stage-wise evidence asymmetry, defines the agri-food digital thread, and proposes comparable measures for excursions, spoilage, traceability completeness, and retrieval latency. Evidence was limited mainly to English-language pilot studies.

Keywords: Internet of Things (IoT), agri-food supply chains, digital thread, performance metrics, cold-chain monitoring, traceability

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1. Introduction

The Internet of Things (IoT) has become an enabling infrastructure for agri-food supply chains (AFSCs), yet evidence of its operational performance remains sparse and uneven across stages. Publications and deployment claims have multiplied, and many of these studies describe an architecture without measuring what it achieves. The resulting evidence gap makes decisions harder for researchers, system designers, operators, and technology purchasers [1, 2]. We address it by synthesising the evidence for each of the seven AFSC stages and proposing a minimum set of metrics for testing and comparing outcome claims.

Food security depends partly on preserving product value after production. Quality and safety can deteriorate as products move through processing, storage, transportation, distribution, and retail, and accountability becomes harder to maintain [3, 4]. AFSCs comprise seven stages: pre-production (input procurement), production (on-farm), processing, storage, transportation, distribution and retail, and consumption. In many settings, weak coordination and limited process visibility impede oversight across organisational boundaries [5, 6]. These weaknesses contribute to food loss and waste, estimated at 30% of global production, and heighten the risk of food-safety failures during supply-chain disruptions [7, 8, 9]. Downstream losses often arise from inadequate temperature and humidity

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control, delayed spoilage detection, and incomplete condition or traceability records at logistics handoffs [6, 10, 11, 12].

Among Fourth Industrial Revolution technologies, the IoT is a core infrastructure for addressing AFSC bottlenecks [1, 13]. IoT systems connect sensors, machines, and digital platforms to capture near-real-time data and link physical assets or products with decision and control systems [14]. In AFSCs, environmental sensors, Global Positioning System (GPS) devices, radio-frequency identification (RFID) tags, quick-response (QR) codes, and cloud- or edge-based analytics can support continuous monitoring and timely corrective interventions [15, 16]. These capabilities help with postharvest compliance monitoring, earlier detection of quality deterioration, end-to-end traceability, and targeted recalls [17, 18].

For engineers, the problem is keeping product condition and identity intact as goods pass through cold rooms, refrigerated vehicles, warehouses, retail outlets, and organisational interfaces [19, 20]. IoT deployments provide instrumentation and control layers for these settings. Sensors generate continuous data streams, and telemetry sends these to a monitoring platform that compares them with predefined thresholds. When a threshold is exceeded, the system can issue an alert or trigger corrective action, such as adjusting a refrigeration set-point or flagging a consignment for inspection [18]. Seen from this angle, IoT deployments are judged by measurable performance under operational conditions, including sensor reliability, power availability, connectivity, and interoperability, rather than by adoption claims [1, 21]. Across AFSC stages, the IoT supports three broad functions: condition monitoring and control, identity preservation and traceability, and decision support and optimisation [18, 22]. These functions depend on communication protocols such as MQTT, CoAP, and AMQP; edge–cloud architectures that balance latency and bandwidth; and open standards such as oneM2M and ISO 22005 for cross-organisational data exchange.

Evidence on outcomes has not kept pace with the growth of IoT research in AFSCs. Relatively few studies report standardised measures, such as excursion frequency, spoilage rate, shelf-life extension, contamination indicators, or traceability completeness [23, 24]. Validation is also uneven across stages: production is studied more frequently than storage, transportation, distribution and retail, or consumption, despite their direct relevance to food loss reduction and food safety [20, 25].

IoT development shows the same imbalance. Early smart-agriculture systems emphasised basic connectivity and monitoring, whereas more recent systems combine advanced sensing, unmanned aerial vehicles (UAVs), and GPS-enabled control to improve on-farm input management and yield [14, 15, 16]. The IoT is also increasingly integrated with artificial intelligence (AI), machine learning, and blockchain to support forecasting, automation, and traceability across multi-actor supply chains [17, 20]. Bibliometric studies show rapid growth in publication volume, but much of the literature still prioritises technology design and conceptual architecture over harmonised, stage-specific outcome measures [18, 22].

Downstream studies also use heterogeneous data-collection methods. Sensor-calibration procedures, sampling windows, alert thresholds, validation measures, and baseline comparators vary enough to limit cross-study comparison [22, 26]. IoT-enabled cold-chain monitoring is widely considered feasible, but reported benefits and trade-offs are context-dependent, and reporting standards remain inconsistent [22, 26]. Field trials show that smart logistics systems can function in real operations, although their findings may not generalise across products, routes, or infrastructure conditions [27]. IoT-based traceability has advanced system design and data capture, but no widely accepted method exists for evaluating traceability completeness or recall performance [28, 29]. Many downstream studies describe prototypes or small pilots while giving limited attention to maintenance cycles, calibration drift, unstable power, connectivity gaps, and human error at logistics handoffs [20, 25, 30].

Consequently, AFSC research remains dominated by feasibility studies and provides limited evidence of downstream effects on food safety, loss reduction, and traceability [24, 31]. The central gap is the absence of an integrated, outcome-oriented evidence base that compares IoT performance across AFSC stages using food-security-relevant indicators. Addressing this gap requires a synthesis that connects thematic development with measurable operational outcomes and treats the IoT as a chain-wide monitoring and control infrastructure rather than a collection of isolated deployments [20, 24, 25].

The review addresses three research questions:

- How did publication output, collaboration patterns, and thematic structure develop in IoT-enabled AFSC research from 2015 to 2025, and which AFSC stages received the most attention?
- What quantified outcomes have empirical studies reported for IoT applications across AFSC stages, and which indicators recur frequently enough to support cross-study comparison?
- Which evidence gaps and system constraints limit downstream performance in the distribution-and-retail and consumption stages? Which stage-appropriate metrics can support a comparable evaluation of food-security-relevant outcomes?

We answered these questions with a dual-method evidence synthesis. Bibliometric analysis of 625 records published from 2015 to 2025 mapped publication growth, collaboration patterns, and thematic structure (RQ1). A systematic review of 68 empirical studies then synthesised stage-specific IoT applications and quantified outcomes (RQ2 and RQ3). Together, the two components identify where measurable benefits have been reported (in resource efficiency, cold-chain integrity, shelf-life preservation, contamination management, and traceability) and where system constraints still limit implementation.

1.1 Contribution and significance

We contribute an integrated, comparative evidence architecture for agri-food IoT in four ways. The first is methodological. By combining bibliometric mapping of 625 records with a PRISMA 2020 systematic review and JBI appraisal of 68 empirical studies, we keep the volume of research activity apart from the strength of quality-appraised performance evidence. The second is empirical: we measure how unevenly that evidence is spread across the seven AFSC stages (strong for production, moderate for storage and transportation, limited for the other four) and test whether the pattern holds after 19 low-quality studies are excluded. The third, conceptual contribution is the agri-food digital thread, defined by the product, condition, and event records that must persist across handoffs and the points at which that continuity fails. Finally, the practical contribution is a set of stage-appropriate measures for spoilage, temperature excursions, traceability completeness, retrieval latency, calibration, connectivity, and interoperability, which researchers, engineers, technology providers, and policymakers can use to check whether reported outcomes are comparable, replicable, and suitable for cumulative evaluation.

We position this contribution against bibliometric and supply-chain reviews; technology- and stage-specific syntheses of smart farming, cold chains, blockchain traceability, and digital twins; and focused pilot, prototype, and EAI application studies. These bodies of work do not integrate quality-appraised operational evidence, a complete seven-stage comparison, sensitivity testing, and a common measurement framework in one synthesis. Sections 4.2 and 4.3 provide the detailed comparison.

Table 1 compares representative empirical and review studies published from 2020 to 2025. It shows what each study contributes, the AFSC stage or technology it covers, and the residual gap addressed by the present review

Table 1. Comparative scope, contribution, and residual evidence gaps in related IoT and AFSC studies

Reference	**AFSC stage or focus**	**IoT application**	**Main contribution**	**Residual gap addressed here**
[2]	Cross-stage supply-chain management	IoT in supply-chain management	Maps publication growth and thematic clusters through bibliometric analysis.	Does not appraise study quality or synthesise stage-specific operational outcomes.
[20]	Transportation and cold-chain supervision	IoT-supported logistics monitoring	Examines IoT-supported supervision of agricultural-product cold-chain logistics.	Provides a transportation-focused application rather than a seven-stage evidence comparison.
[25]	Food safety and traceability	Blockchain-enabled food supply-chain management	Synthesises blockchain applications for food safety and traceability.	Focuses on one technology class and does not establish comparable IoT outcome measures across stages.
[26]	Cold-chain logistics	Internet of Everything and digital-twin service platform	Proposes an integrated service platform for cold-chain logistics.	Emphasises platform architecture rather than quality-appraised, cross-stage outcome evidence.
[29]	Cross-stage traceability	Blockchain, IoT, and AI	Reviews convergent technologies for enhanced traceability systems.	Highlights technical integration but does not benchmark traceability completeness or retrieval latency across stages.
[32]	Fresh-food traceability	IoT-based traceability systems	Develops policy-oriented guidance for aligning fresh-food traceability with sustainability goals.	Does not validate a common set of field-performance indicators across the AFSC.
[33]	Food-quality management	Industry 4.0 tools, including IoT	Links Industry 4.0 capabilities to food-quality-management functions through a review-based framework.	Reports uneven empirical evidence and does not compare outcome strength across all AFSC stages.
[34]	Storage and transportation	Cold-chain monitoring technologies	Reviews the development and management of food cold-chain logistics.	Identifies implementation challenges but does not provide a quality-appraised cross-stage synthesis.
[35]	Cross-stage supply-chain management	IoT-based supply-chain management	Systematically reviews IoT supply chain management research published from 2018 to 2022.	Does not disaggregate validated outcomes across all seven AFSC stages or propose stage-specific metrics.
[36]	Transportation	Real-time cold-chain monitoring	Demonstrates real-time IoT temperature monitoring in a container-port setting.	Provides single-setting observational evidence without long-term spoilage or cross-stage validation.

2. Methodology

This study combined bibliometric analysis with a systematic literature review (SLR). The SLR synthesised empirical evidence on IoT interventions and quantified outcomes related to food quality, safety, traceability, and resource use across all AFSC stages. The bibliometric component mapped publication trends and thematic patterns to position the SLR within the broader literature. An a priori protocol specified the objectives, eligibility criteria, search strategy, screening workflow, data extraction, and quality appraisal. The SLR was reported in accordance with PRISMA 2020; the complete identification and selection flow appears in Section 3.2.

2.1 Search strategy and information sources

Scopus, Web of Science, and Google Scholar were searched for peer-reviewed English-language literature published between 1 January 2015 and 29 October 2025. The search combined terms relating to IoT, AFSCs, and outcomes in food quality, food safety, and traceability. Backward and forward citation chasing was also performed. Together, the database searches and citation chasing produced a consolidated pool of 630 records. The following core Boolean logic was adapted for each platform.

("Internet of Things" OR "IoT") AND ("agriculture" OR "agri-food" OR "agrifood" OR "food supply chain" OR "agricultural food supply chain") AND ("food quality" OR "food safety" OR "cold chain" OR "postharvest" OR "traceability" OR "spoilage" OR "storage" OR "shelf-life" OR "contamination").

Both components drew on one shared conceptual search strategy across Scopus, Web of Science, and Google Scholar. The publication period, search date, concept blocks, and core Boolean logic were identical, while platform-specific syntax was used: TITLE-ABS-KEY in Scopus, TS= in Web of Science, and an equivalent free-text query in Google Scholar. Google Scholar screening and backward and forward citation chasing formed part of the supplementary discovery process; no separate component-specific search was conducted. The first 100 Google Scholar results were screened in relevance order, and potentially eligible records were captured individually in Zotero. All searches and citation chasing were completed on 29 October 2025. The archived record preserves the final consolidated pool and identifies five records contributed only through Google Scholar or citation chasing, but it does not retain complete source-specific retrieval counts or the exact overlap between the first 100 Google Scholar results and indexed database records.

Scopus and Web of Science records were exported as RIS and imported into Zotero. Google Scholar records were captured individually because the structured metadata required by VOSviewer and Bibliometrix was unavailable. For the SLR, automated duplicate detection combined with manual DOI, title, year, author, and source matching removed 238 duplicates, leaving 392 records. Separately, 625 Scopus and Web of Science records with complete abstracts, keywords, citation data, and authorship metadata formed the record-level bibliometric corpus before cross-source deduplication. Five Google Scholar or citation-chasing records lacked complete bibliometric metadata; they remained eligible for SLR screening but were excluded from mapping. Thus, the bibliometric strand used record-level publication and network mapping, whereas the SLR used deduplicated study-level screening. Appendix A reports the syntax, processing, provenance limitations, and count reconciliation.

2.2 Eligibility criteria

The eligibility criteria were structured according to the PICO framework. The population or setting comprised stakeholders and contexts across seven AFSC stages: pre-production, production, processing, storage, transportation, distribution and retail, and consumption. Eligible interventions included IoT technologies, such as sensors, RFID, wireless networks, GPS devices, smart devices, and connected monitoring systems, used to monitor, control, or optimise food quality, safety, traceability, or resource use. Comparators included conventional or control practices without IoT. Non-comparative designs were retained when relevant quantitative outcomes were reported. Eligible outcomes comprised physical, chemical, or biological measures of food quality and safety, as well as traceability, monitoring completeness, resource efficiency, yield, spoilage, and shelf-life. Conceptual papers, narrative reviews, editorials, studies outside agricultural supply chains, and studies without relevant quantitative outcomes were excluded. The same criteria were applied during title and abstract screening and full-text assessment.

2.3 Study selection and screening

After 238 duplicates were removed, two reviewers screened the titles and abstracts of 392 records. A pilot exercise calibrated the interpretation of the eligibility criteria. Inter-rater agreement was strong (Cohen's $\kappa = 0.81$), and disagreements were resolved by discussion and consensus. Of the 392 records, 84 reports were sought for retrieval; two were unavailable, and 82 were assessed in full text. Fourteen full-text reports were excluded: eight lacked a relevant quantitative outcome, four fell outside the agricultural supply-chain context, and two were duplicate reports of the same study. The remaining 68 studies entered the systematic review. The complete selection flow is reported in Section 3.2.

2.4 Data extraction, quality appraisal, and synthesis

The co-authors extracted data from the 68 included studies using a standardised, pilot-tested data extraction form. The variables included study location, AFSC stage, study design, IoT technology and intervention, comparator where available, quantitative outcomes, and primary findings. Disagreements were resolved by consensus, and study authors were contacted for clarification when necessary. The data were tabulated and synthesised narratively. Table 2 presents the stage-level profiles. Appendix B provides the extraction framework, coding guidance, and JBI appraisal domains.

Methodological quality was assessed with the Joanna Briggs Institute (JBI) critical appraisal checklist appropriate for each study design. Disagreements were resolved through discussion, with an independent reviewer consulted when necessary. A sensitivity analysis excluded 19 low-quality studies, leaving a restricted corpus of 49. The most frequent weaknesses were the absence of a formal comparator or control condition (n = 14), an undefined or non-standardised outcome measure (n = 11), and an inadequate description of participants or settings (n = 9); individual studies could have deficiencies in more than one domain. Exclusion did not alter the overall interpretation: production retained the strongest evidence, storage and transportation retained moderate evidence, and both the distribution-and-retail stage and the consumption stage remained underrepresented. Verified stage-specific exclusion counts were unavailable and are therefore not reported. Appendix C presents the evidence-strength classifications and verified aggregate counts. The bibliometric parameters were not subjected to sensitivity analysis.

Narrative synthesis was selected because substantial heterogeneity in study design, interventions, comparators, outcome definitions, and reporting precluded a meaningful pooled effect estimate [37]. The evidence was organised by AFSC stage and summarised by outcome direction, comparator design, and practical implications. Table 2 presents a stage-level profile that classifies the evidence as high, moderate, or limited, and identifies the predominant technologies and study designs.

Table 2. Stage-level characteristics and evidence profile of the 68 included studies

AFSC stage	Number of studies	Predominant IoT technologies	Typical study design	Typical comparator or baseline	Evidence strength and interpretation
Pre-production (input procurement)	8	Remote sensing and data dashboards	Decision-support evaluations, small pilots, and case-based implementations focused on input ordering or authenticity	Usually no formal comparator; where reported, manual procurement was compared with dashboard-assisted workflows	Limited: evidence focused mainly on climate modelling and input optimisation
Production	21	Smart irrigation, soil sensors, and UAVs	Field trials, quasi-experimental studies, and before-and-after evaluations of sensing and actuation	Conventional practice, including manual irrigation or fertilisation, calendar scheduling, or farmer judgement	High: the most consistent evidence concerned yield and water-use efficiency
Processing	7	Sensor-integrated machinery	Small pilots, prototype tests, and laboratory or bench validation of sorting and process-monitoring functions	Manual inspection or sorting, a process line without IoT sensing, or no explicit comparator	Limited: evidence was concentrated in small-scale process automation
Storage	8	Wireless sensor networks for temperature and humidity	Field monitoring in cold rooms or warehouses, often with alerting; some observational evaluations linked monitoring to quality outcomes	Manual logs or spot checks, or pre–post comparison after monitoring was introduced	Moderate: monitoring conditions improved, with some direct evidence of quality outcomes
Transportation	9	RFID, GPS, and cold-chain sensors	Operational pilots and logistics-monitoring evaluations involving telemetry and traceability	Periodic checks or paper logs; some pre–post comparisons of excursion frequency or duration	Moderate: evidence supported improved traceability and excursion management
Distribution and retail	8	QR- and RFID-based consumer interfaces	Case studies, platform demonstrations, and architecture-led implementations, often combining IoT with blockchain	Paper-based traceability was commonly described, but a measured baseline was often absent	Limited: transparency was emphasised, but few studies measured operational effects
Consumption	7	Smart appliances and consumer applications	Exploratory prototypes, usability or behaviour trials, and small observational studies of household food tracking	Self-reported usual household practice, generally without a controlled comparator	Limited: evidence was exploratory and rarely linked to food-security outcomes

Abbreviations: AFSC, agri-food supply chain; GPS, Global Positioning System; QR, quick-response code; RFID, radio-frequency identification; UAV, unmanned aerial vehicle; WSN, wireless sensor network

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2.5 Bibliometric analysis

The bibliometric analysis used record-level metadata, including authors, affiliations, sources, keywords, abstracts, and citations, which were processed using VOSviewer and the Bibliometrix R package [38, 39]. Spelling variants, plural forms, hyphenated variants, and unambiguous synonyms were consolidated prior to the analysis. Co-authorship and author-keyword co-occurrence networks were generated after filtering sparse nodes for interpretability. Bibliometrix was used to calculate the annual record output, source and author rankings, and thematic structure. Build-specific software versions, exact network thresholds, and clustering resolution values were not retained in the archived record and are therefore not reported. Because cross-source duplicates were removed only for the SLR pathway, bibliometric outputs were interpreted as descriptive maps of database-record growth, geographic participation, author-keyword relationships, and thematic structure, not as counts of unique studies or inferential evidence.

3. Results

3.1 Bibliometric results

Database-indexed publication output on the IoT in agriculture and food security increased markedly from 2015 to 2025 (Figure 1). Annual output rose from one or two records per year during 2015–2017 to 9 in 2018, 15 in 2019, 19 in 2020, 48 in 2021, 55 in 2022, 108 in 2023, and 190 in 2024; output also remained high during the partial 2025 search period. Publication output was concentrated in India and China, with the United States and the Netherlands also prominent. The three-field plot in Figure 2 links author countries, authors, and author keywords, and shows the geographic and thematic concentration of the literature. This concentration suggests that research capacity is unevenly distributed, which is one argument for wider international collaboration [40].

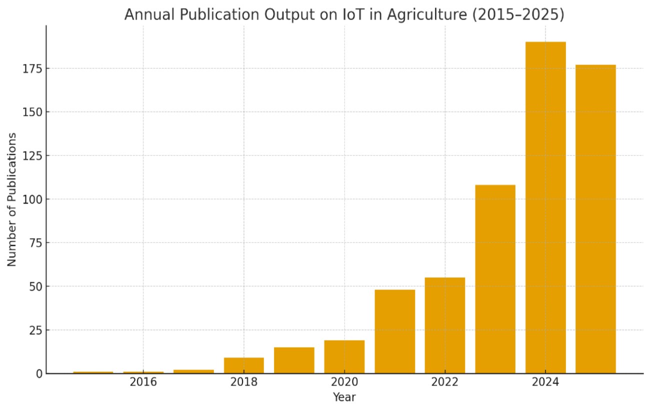

Figure 1. Annual publication output of IoT in agriculture and food security, 2015–2025. Source: Authors' analysis

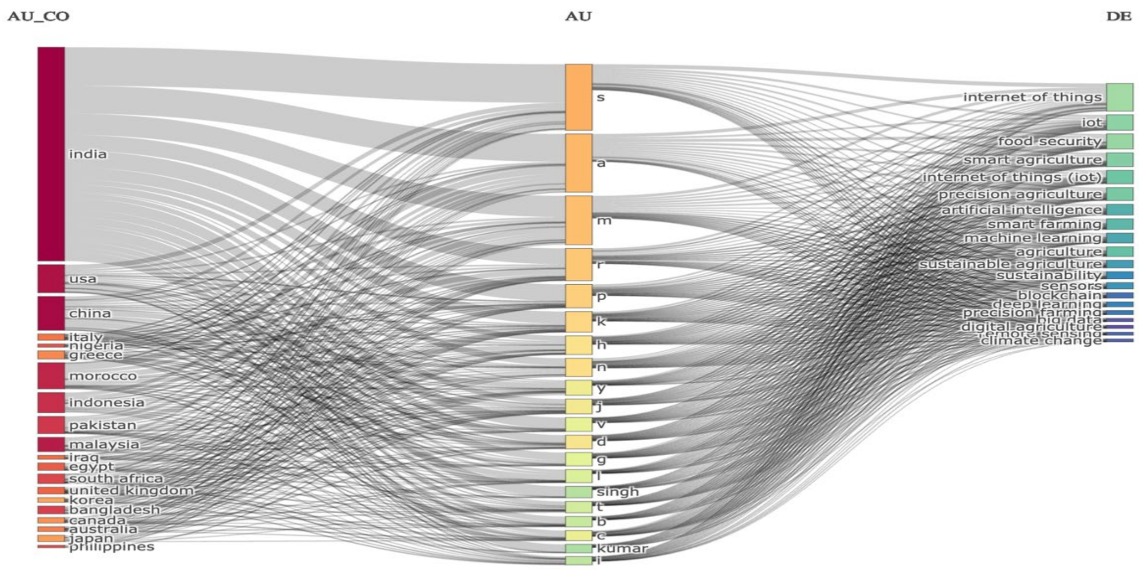

Figure 2. Three-field plot linking author countries, authors, and author keywords in IoT-enabled agri-food supply-chain research, 2015–2025. Source: Authors' analysis

The strategic thematic map (Figure 3) spans sensor networks and infrastructure, AI-enabled decision support, automation, sustainability, and food traceability. The horizontal axis represents centrality, or the degree of interaction between a theme and other themes, and the vertical axis represents density, or internal thematic development. Themes in the upper-right quadrant are both central and well-developed (motor themes); those in the lower-right are central but less cohesive (basic or transversal themes); those in the upper-left are well-developed but peripheral (niche themes); and those in the lower-left are peripheral and underdeveloped (emerging or declining themes). Blockchain, big data, machine learning, and computer vision fall in the motor quadrant, so these analytics and trust-related themes are both central to the field and internally well developed. However, thematic prominence does not imply equivalent validation of outcomes across AFSC stages.

Two bibliometric patterns motivated the systematic review. Annual records grew from fewer than five per year before 2018 to 190 in 2024, which shows rising research attention but not whether outcome evidence accumulated at the same rate. Thematic clustering around sensor networks, AI, and traceability confirms the field's technological focus without showing where outcomes have been measured or validated across AFSC stages. Answering that question requires a stage-disaggregated synthesis of reported outcomes, which the PRISMA-compliant systematic review in Section 3.2 provides.

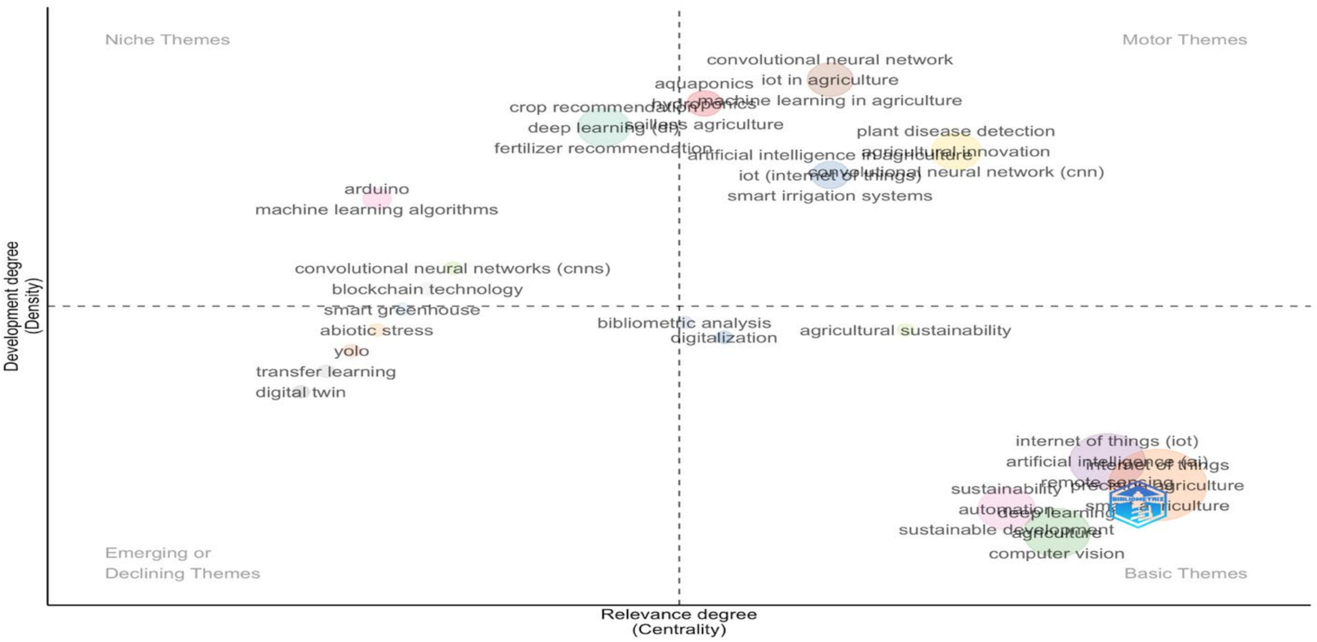

Figure 3. Strategic thematic map of author keywords in IoT-enabled agri-food supply-chain research. The horizontal axis represents centrality (interaction with other themes), and the vertical axis represents density (internal thematic development). Motor themes (upper right) are central and well developed; niche themes (upper left) are well developed but peripheral; basic themes (lower right) are central but less cohesive; and emerging themes (lower left) are peripheral and underdeveloped. Source: Authors' analysis

3.2 Systematic review results

Figure 4 summarises the shared discovery process and the subsequent divergence between the record-level bibliometric corpus and the deduplicated, study-level systematic-review pathway.

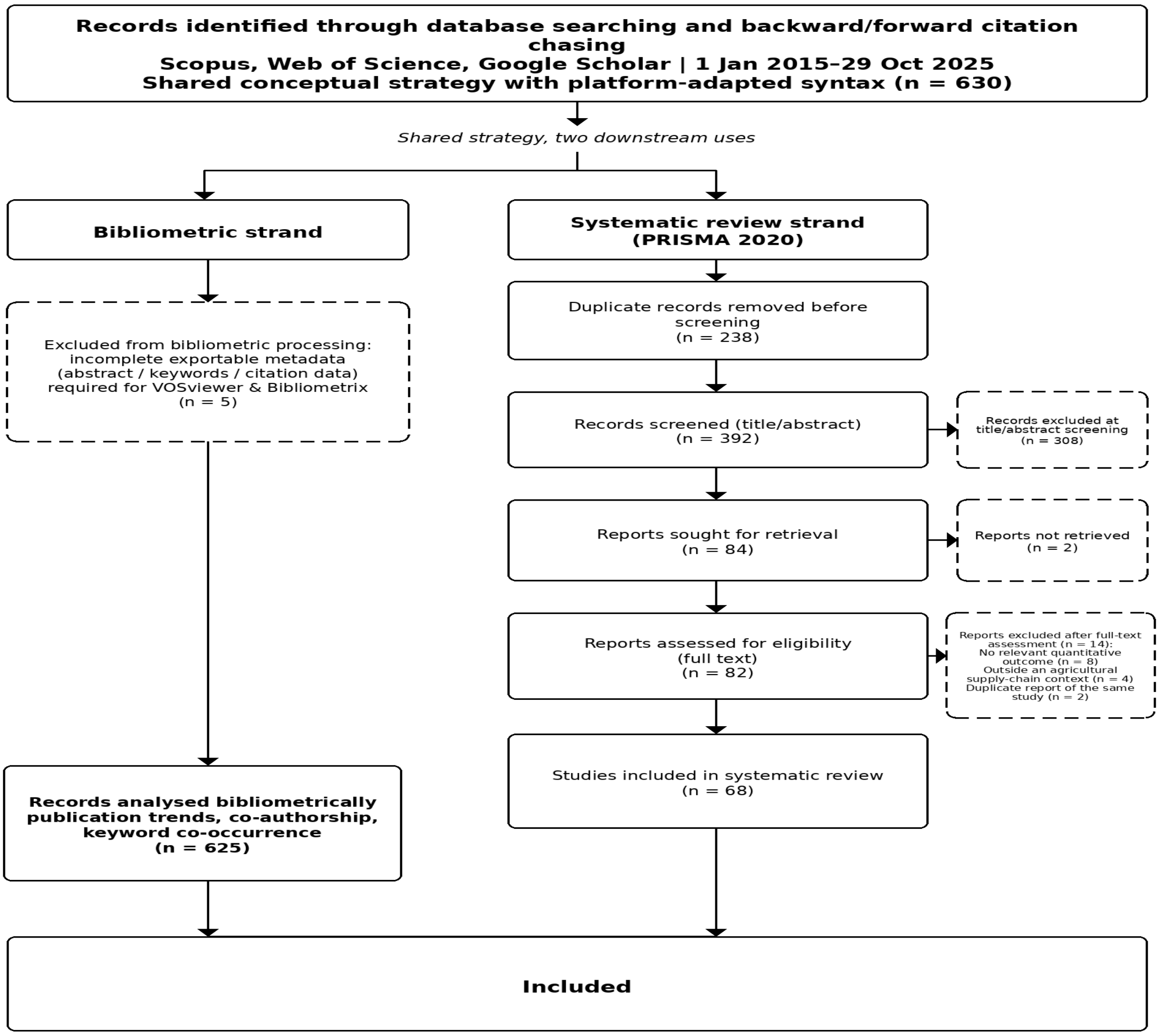

Figure 4. Identification and selection flow for dual-method synthesis. Database searches in Scopus, Web of Science, and Google Scholar, supplemented by backward and forward citation chasing, produced a consolidated pool of 630 records for review. The bibliometric strand retained 625 Scopus and Web of Science records as a record-level corpus before cross-source deduplication for descriptive mapping. The PRISMA 2020 systematic review strand removed 238 duplicates, screened 392 unique records, assessed 82 full-text reports, excluded 14 reports (no relevant quantitative outcome, n = 8; outside an agricultural supply-chain context, n = 4; duplicate report of the same study, n = 2), and included 68 studies. Source: Authors' analysis, adapted from Page et al. [41]

The systematic review included 68 studies across all seven AFSC stages: eight in pre-production, 21 in production, seven in processing, eight in storage, nine in transportation, eight in distribution and retail, and seven in consumption (Table 2). The technologies varied by stage. Pre-production studies used remote sensing and data dashboards; production studies used smart irrigation, soil sensors, and UAVs; processing studies used sensor-based sorting and monitoring; storage and transportation studies used multisensor cold-chain networks; and distribution-and-retail studies used RFID, QR, and blockchain-enabled platforms. Most studies were small pilots or field trials; where comparators were available, they typically involved conventional practice or pre–post baselines.

3.3 Stage-wise findings

Pre-production (input procurement): Evidence was limited and insufficient for quantitative synthesis. Applications included automated ordering, RFID-enabled tracking of seeds and fertilisers, and dashboards for input quality and authenticity. These systems were intended to improve procurement efficiency and traceability [42], but most studies were uncontrolled demonstrations that reported few quantitative outcomes.

Production (on-farm): This stage had the strongest evidence base. Prototype wireless sprinkler systems demonstrated technical functionality, but comparative yield data have not yet been reported [43]. A broader review of IoT in agriculture described productivity benefits without a study-specific percentage [44]. UAV imagery supported the earlier detection of pests and diseases and, in some studies, reduced pesticide use [44, 45]. Livestock wearables were associated with earlier disease detection, improved feeding management, and lower mortality risk [46]. Field studies integrating nutrient management, crop-status monitoring, and irrigation management reported improvements in water productivity and crop yield [47]. In a two-year soybean field study by Sachin et al. [47], sprinkler irrigation at 80% of crop evapotranspiration produced grain yields 23.1–29.1% higher than those under flood irrigation. This author-reported comparison was study-specific and not pooled. The stronger evidence base for production likely reflects the longer history and greater measurability of precision agriculture on farms.

Processing (postharvest handling and processing lines): Evidence was sparse and largely confined to small-scale pilots. The included systems combined computer vision with sensor arrays to monitor temperature, pH, contamination indicators, and related variables during sorting or processing. These applications may improve process consistency and reduce manual recording errors [48, 49]. Real-time pH and temperature monitoring can identify deviations before the product is released [50]. Closed-loop systems have been reported to improve quality and throughput and to reduce waste, but rigorous controlled evaluations remain uncommon and process-specific [50].

Storage (cold rooms and warehouses): Evidence was moderate and generally indicated improved monitoring. Sensor networks measure temperature, humidity, and gas concentrations in cold-storage environments [51], and alert systems allow earlier decisions on maintenance, stock rotation, or product segregation [52]. Afreen and Bajwa reported fewer and shorter off-temperature events after the introduction of automated monitoring and alerting [51]; this was a pre–post observational study without a controlled comparator.

Transportation (refrigerated transport): The evidence was moderate. Telemetry combines environmental measurements with GPS data to support continuous cold-chain monitoring and traceability [53]. At a refrigerated container port, Cil et al. found that automated alerts shortened the interval between deviation onset and corrective intervention compared with periodic manual inspections [36].

Taken together, the storage and transportation studies associated real-time alerting with better excursion detection and response. Their observational designs, however, do not justify a pooled percentage reduction or a general causal claim about spoilage [36, 51, 54].

Distribution and retail (traceability and identification): Evidence was limited and largely case based. The IoT is often combined with blockchain to record events across production, processing, transport, and retail, with the aim of improving transparency and reducing fraud [55, 56]. QR- or RFID-based smart labels enable access to product histories at the point of sale [57]. Studies rarely report standardised measures of traceability completeness, retrieval latency, recall precision, or waste reduction. Recent studies have proposed such indicators, but few have evaluated their operational effects in the field.

Consumption (consumer interface): Evidence at this stage was exploratory. Applications included freshness-sensitive packaging, smart appliances, and household inventory tools designed to reduce food waste [58]. These systems were intended to alert consumers to approaching spoilage or support meal planning, but field evidence linking their use to measurable food-security outcomes remained limited.

Overall, production had the clearest quantified evidence, and storage and transportation had moderate, mostly observational evidence of improved monitoring and excursion management [1, 59]. The distribution-and-retail stage and the consumption stage remained understudied and poorly standardised, although recent work has proposed more concrete performance measures for both stages [60]. The pattern points to the digital-thread concept developed in Section 4.1: when identification, sensing, and event records are complete and interoperable, product identity and condition can be followed across handoffs to support quality, safety, and accountability.

4. Discussion

The evidence associates IoT deployment with more precise on-farm resource use, earlier detection of postharvest quality deviations, and stronger traceability where event records are complete. Because much of the evidence is case-based or observational, these associations should not be interpreted as general causal effects.

4.1 Operational definition: the digital thread and outcome metrics

In this review, a digital thread is defined as the end-to-end continuity of product and process data across an AFSC. It is created through IoT-enabled identification (such as RFID or QR codes), sensing of variables such as temperature, humidity, or gas concentration, and event capture at harvest, grading, storage entry and exit, shipment, and receipt. The digital thread specifies which data persist, where they originate, and how they can be retrieved for quality assurance, loss reduction, and accountability. Unlike a digital twin, which uses data to model, simulate, or optimise an asset or process, a digital thread preserves linked records across stages and handoffs.

Combined with digital twins, AI, and edge–cloud computing, IoT data streams can support near-real-time modelling, early intervention, and scenario-based planning [61, 62, 63], although effectiveness depends on data quality, interoperability, and institutional capacity.

To improve comparability and evidence accumulation, studies should report a minimum set of stage-appropriate outcome metrics.

Cold-chain integrity: frequency of temperature excursions, cumulative time outside specifications, mean kinetic temperature, and proportion of consignments meeting compliance thresholds [64].

Loss and shelf-life: spoilage rate, expressed as percentage mass loss or rejected units; shelf-life extension in days; and quality retention measures such as firmness, colour, and soluble solids content, each reported against an explicit baseline [65].

Safety and contamination control: number of verified contamination or authenticity events, microbial or chemical indicators measured, and time from deviation to detection or intervention [66].

Traceability performance: completeness, defined as the proportion of units with a full event history, retrieval latency, recall precision, and total recall time [67, 68].

Operational performance: inventory accuracy, stock-out frequency, shrinkage between receipt and sale, and energy intensity of cold storage or transport per unit handled [69].

These outcomes should be reported with implementation descriptors, including sensor type and placement, sampling frequency, calibration and quality-assurance procedures, connectivity and power constraints, and baseline conditions. This information would make digital thread claims empirically testable and make future meta-analyses more feasible.

4.2 Comparative positioning and journal-specific contribution

Prior reviews fall into three groups, each useful but incomplete. Rejeb et al. [2] map publication trends and thematic clusters, while Taj et al. [35] synthesise IoT supply chain management research published from 2018 to 2022. Other reviews are limited to smart farming, cold-chain management, or blockchain–IoT traceability [28, 29]. These studies establish rapid growth and recurring implementation challenges, but they do not jointly appraise quantified outcomes across all seven AFSC stages, test whether conclusions remain stable after quality-based exclusions, or translate the evidence into a cross-stage reporting standard. Broader digital-twin studies [70, 71] likewise identify validation deficits but do not provide a stage-disaggregated performance benchmark.

Within EAI Endorsed Transactions on Internet of Things, Truong et al. [72] designed a LoRa- and blockchain-based system for monitoring agricultural products during transportation; Karthikeyan and Nagaprakash [73] used qualitative retail cases to prioritise IoT-enabled sustainability initiatives; and Balamurugan et al. [74] reported that animal-detection performance increased from 55% to 79% with an IoT- and convolutional-neural-network-based crop-protection system. Each makes a focused contribution at a single stage. Their designs, however, do not provide a common basis for comparing outcome validity, traceability completeness, retrieval latency, or implementation quality across the agri-food chain. They are cited here for journal-specific positioning and were not retrospectively added to the screened 68-study corpus.

Against this literature, the present study contributes an evidence architecture. It separates the mapping of 625 records from JBI-appraised outcome evidence in 68 studies; compares evidence strength across seven stages and retests the pattern after excluding 19 low-quality studies; operationalises the digital thread as continuity of identity, condition, and event records across handoffs; and defines a minimum metric set that makes future claims testable and comparable.

4.3 Benchmarking against state-of-the-art frameworks and deployments

Representative deployments further clarify the distinction between technical functionality and validated operational outcomes. Cil et al. [36] reported that automated temperature alerts at a refrigerated container port shortened the interval between excursion onset and operator response relative to periodic manual inspection. This observational pilot supports an excursion-response metric but does not establish a spoilage-reduction effect. Afreen and Bajwa [51] reported fewer and shorter off-temperature events after automated cold-storage monitoring was introduced. That result supports excursion frequency and duration as metrics, although the study lacked a controlled comparator. Sachin et al. [47] compared sprinkler-irrigated soybean yields with flood irrigation over two years (Section 3.3). By contrast, Venkatesh et al. [43] presented a smart-sprinkler prototype without comparative yield data, and Mentsiev et al. [44]

described general productivity benefits without a study-specific percentage. The EAI studies illustrate the same distinction: Truong et al. [72] demonstrated LoRa sensor capture and blockchain-backed records during transportation but did not report field-scale traceability completeness, recall precision, or loss reduction; Balamurugan et al. [74] quantified animal-detection performance at the production stage but not yield, product loss, or downstream data continuity; and Karthikeyan and Nagaprakash [73] identified retail sustainability benefits from qualitative case analysis, without standardised retail outcome measures. Reviews of blockchain–IoT traceability [75, 76] similarly describe what the technology can do but seldom report retrieval latency, chain-of-custody completeness, or recall precision under field conditions. The proposed measures therefore provide a common basis for distinguishing system operation from verified AFSC performance.

4.4 Barriers to scalable and inclusive deployment

Four barriers limit the scale and inclusiveness of IoT implementation:

Techno-economic barriers: High capital costs and recurring expenditures for maintenance, connectivity, and data management may be prohibitive for smallholders, particularly when credit is limited and returns on investment are uncertain [77].

Infrastructure barriers: Many rural areas lack reliable electricity and connectivity, both of which are prerequisites for continuous or near-real-time IoT operations [78, 79].

Data governance and security barriers: IoT systems generate large volumes of operational and personal data that require secure storage, controlled access, and responsible use. Unclear ownership, weak privacy protection, and cybersecurity risks can discourage data sharing and adoption [50, 80].

Human and organisational barriers: Limited digital literacy, weak technical support, and resistance to organisational change can constrain adoption. Participatory design, user training, and technical and extension support are needed to build trust and sustain capability [81, 82].

Social sustainability and equity: Beyond these four barriers, IoT-enabled traceability may improve recall targeting and consumer confidence by helping operators identify affected lots more rapidly [66]. Automation may also reduce exposure to repetitive and hazardous monitoring tasks. However, high acquisition and maintenance costs, limited digital skills, and unequal access to infrastructure may deepen the disadvantages faced by smallholder farmers [83], and uneven access to finance, technical knowledge, advisory support, and organisational resources can further restrict their participation in digital agriculture. Targeted capacity building and inclusive policy design are therefore needed [84].

Environmental and economic implications: Smart irrigation and variable-rate application can reduce excessive water and agrochemical use, with potential benefits for soil health and biodiversity [85, 86]. Condition monitoring can reduce spoilage and associated greenhouse-gas emissions [87], while data-informed decisions may lower input costs, improve yields [44], and reduce avoidable losses [88, 89]. These benefits must be weighed against the environmental costs of hardware manufacturing, energy use, and electronic waste, and against unequal access [1]. A UK frozen-food case reported lower waste after broader digital monitoring and operational controls, but it did not isolate the effect of IoT cold-chain monitoring [88].

4.5 Agricultural-engineering implications and design requirements

Across AFSC stages, IoT performance evidence is most comparable and transferable when deployments are treated as calibrated, interoperable monitoring and control systems. The digital-thread concept clarifies the engineering requirements for preserving product identity and condition records across handoffs. The following requirements are organised by subsystem:

4.5.1 Cold-storage monitoring (storage)

- **Sensor placement and calibration:** Sensors should be placed to capture spatial gradients, including near evaporator coils and doors, rather than using a single averaged reading. Reports should specify the calibration, drift-detection, and replacement procedures because even small sensor biases can affect compliance assessment and shelf-life prediction [90].
- **Alerts and control:** Escalation thresholds, such as cumulative time outside specifications or repeated excursions, should be defined, and each threshold should be linked to an operational response, including maintenance, set-point adjustment, stock segregation, or inspection.

4.5.2 Telemetry for refrigerated transport (transportation)

- **Data integrity under intermittent connectivity:** Deployments should use store-and-forward logging, reliable timestamps, and explicit procedures for identifying and handling missing data.
- **Comparability:** The sampling interval, excursion-counting rule, and compliance threshold should be reported so that results from different deployments can be compared on a common basis.

4.5.3 Processing-line sensing and control (processing)

- **Sensor-to-control integration:** Reports should distinguish variables used only for monitoring or advisory alerts from those linked to closed-loop control and should state the time from detection to intervention.
- **Reproducibility:** Reports should specify sensor locations, sampling points, hygienic design constraints,

and measurement procedures for variables such as pH, temperature, and microbial indicators.

4.5.4 Traceability and identification (distribution and retail)

- **Event completeness:** Deployments should define the traceable unit, such as a lot or an individual item, and the required event types, including harvest, grading, storage entry and exit, shipment, and receipt.
- **Interoperability:** Open identifiers and standardised event schemas should be used to prevent traceability records from fragmenting across organisational boundaries.

4.5.5 Minimum reporting standard (cross-cutting)

Reports should define the system boundary and covered assets, specify the sensor or identifier type and placement, state the sampling rate and procedures for managing missing data, describe calibration, quality-assurance, and maintenance procedures, document the connectivity and power constraints, explain the alert logic, and report the prespecified outcome metrics. These details are necessary for comparison, replication, and evidence synthesis.

Illustrative worked example (refrigerated transport corridor). This example synthesises design principles, not a single deployment. In refrigerated transport, calibrated temperature and humidity sensors at the evaporator, container midpoint, and door sample every five minutes. Store-and-forward logging preserves timestamps during connectivity loss. When cumulative time outside a specified temperature range exceeds a threshold, the platform alerts the driver and depot manager; at receipt, the event log, GPS track, interventions, and final temperature reading are incorporated into the product's digital-thread record. These data enable calculation of mean kinetic temperature, excursion duration, compliance rate, and the chain-of-custody measures proposed in Section 4.1. Reports should also document sensor drift, buffer overflow, unrecorded interventions, and incompatible warehouse data formats. Applying the minimum reporting standard to these parameters would make corridor deployments comparable.

5. Limitations and research implications

The search covered English-language peer-reviewed publications from 2015 to 2025, so non-English and niche applications may be underrepresented. Google Scholar supplemented the structured database searches, but its opaque ranking algorithm limits reproducibility. Google Scholar records without complete structured metadata were excluded from the bibliometric analysis.

As noted in Section 2.1, the archived record does not retain complete source-specific retrieval counts or the exact overlap among Google Scholar, Scopus, Web of Science, and citation-chasing records. Because the 625 bibliometric records were not deduplicated across sources, their counts and network maps may include duplicate database representations and should not be read as counts of unique studies. Build-specific software versions and exact network and clustering settings were also unavailable, so the bibliometric results remain descriptive.

The sensitivity analysis retained verified aggregate counts (68 included studies, 19 low-quality exclusions, and 49 studies in the restricted corpus), but stage-specific exclusion counts were unavailable. The SLR excluded purely qualitative studies and studies reporting only socioeconomic outcomes, which narrowed the range of perspectives represented. Publication bias may also inflate the apparent frequency of positive outcomes because null findings are less likely to be published or indexed. Full-text exclusion reasons are reported in Section 2.3 and Figure 4.

The evidence quality and coverage were uneven across the AFSC stages. The distribution-and-retail stage and the consumption stage were represented by relatively few studies, and heterogeneous designs limited the generalisability of stage-level conclusions. The JBI appraisal identified recurrent weaknesses in comparator design, outcome definition, and the description of participants or settings. Most studies were short-term pilots or case studies, and few assessed long-term or large-scale operational outcomes.

Beyond the longer, multi-site field evaluations recommended in Section 6.1, interdisciplinary research is needed on capacity building, data governance, cybersecurity, and the life-cycle environmental burden of IoT hardware, including energy use and electronic waste. Testing effectiveness and equity under real-world operating conditions will require collaboration among engineers, social scientists, policymakers, technology providers, and user communities.

6. Conclusion and recommendations

This synthesis of 625 bibliographic records and 68 empirical studies show a clear stage-wise asymmetry. Production provided the strongest evidence. A two-year soybean field study reported 23.1–29.1% higher grain yield under sprinkler irrigation at 80% crop evapotranspiration than under flood irrigation; this was a study-specific comparison, and no pooled yield estimate was calculated. Storage and transportation provided moderate observational evidence that real-time alerts improved excursion detection and response. The distribution-and-retail stage and the consumption stage remain sparsely validated, limiting conclusions about end-to-end supply-chain performance.

The digital-thread framework treats the IoT as a continuous data backbone that preserves product condition and identity across organisational boundaries (Section 4.1). Moving from feasibility demonstrations to outcome-verified deployment requires the outcome metrics and implementation descriptors from that section to be reported in a standard way. Comparative synthesis and evidence-based policy-making both depend on that reporting.

6.1 Stakeholder recommendations

Policy and regulation. Given the barriers in Section 4.4, governments should invest in rural broadband and reliable electricity, provide targeted financial support to resource-constrained users, harmonise data-governance requirements, integrate digital agriculture into extension services, and define end-of-life responsibilities for IoT hardware.

Industry and technology providers. They should design affordable and interoperable systems for resource-constrained settings, evaluate pilots against prespecified metrics from Section 4.1 and the reporting standard in Section 4.5, support open standards that reduce vendor lock-in, and establish clear safeguards for data access, ownership, privacy, and benefit-sharing.

Research. To close the stage-wise evidence gaps in Section 3.3, particularly in the distribution-and-retail and consumption stages, researchers should conduct long-duration, multi-site field evaluations; apply the standardised outcome measures and implementation descriptors proposed in Section 4.1; use controlled or well-defined baselines where feasible; develop context-appropriate cybersecurity approaches; and incorporate life-cycle assessment into hardware and system design.

6.2 Forward outlook

Scaling IoT requires technical systems and institutional capacity to develop together. Reliable rural connectivity, stable power, affordable hardware and finance, user training, ongoing maintenance, and transparent data governance decide whether pilot benefits last. Without them, IoT systems are unlikely to move beyond small pilots or deliver measurable food-security benefits at scale.

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Appendix A: Dual-method search and analysis protocol

This appendix documents the verified search and analysis procedures for the two components of the dual-method evidence synthesis. The components used one shared conceptual search strategy with platform-adapted syntax and diverged during downstream processing: the bibliometric component retained a record-level Scopus and Web of Science corpus for descriptive mapping, whereas the SLR component removed duplicates before study-level screening. Where build-specific software settings were not retained, the appendix reports only verifiable procedures and does not infer any defaults.

A.1. Shared literature search

The bibliometric analysis and SLR used one shared conceptual search strategy. The publication period, search date, concept blocks, and core Boolean logic were consistent, whereas the field codes and query syntax were adapted to Scopus, Web of Science, and Google Scholar. No separate component-specific search was conducted. Google Scholar screening and backward and forward citation chasing were part of the shared search and supplementary discovery strategy. The archived record preserves the consolidated 630-record pool and identifies five records contributed only through Google Scholar or citation chasing, but it does not preserve the complete raw source-specific retrieval counts or the exact allocation of overlapping records.

Parameter	Specification
Databases	Scopus, Web of Science (WoS), and Google Scholar, using one shared conceptual strategy with platform-adapted syntax
Search date	29 October 2025
Publication period	1 January 2015 to 29 October 2025
Language restriction	English-language publications only
Document types	Peer-reviewed articles, reviews, and conference papers in Scopus and WoS. The first 100 relevance-ranked Google Scholar results were screened, and records judged to be potentially eligible were captured; Google Scholar does not provide an equivalent document-type filter.
Search fields	Scopus: TITLE-ABS-KEY; WoS: TS=; Google Scholar: equivalent free-text query without field tags
Records retrieved at record level	630
Duplicates removed for the SLR pathway	238, identified through Zotero's automated detection and manual review using DOI, title-year, and author-source matching; this deduplication produced 392 unique records for SLR screening
Citation chasing	Backward and forward citation chasing of the included studies and key reviews.

A.2. Boolean search string

The same three concept blocks and core synonyms were retained across platforms, whereas field codes and syntax were adapted to each database.

Core string (platform-agnostic logic)
("Internet of Things" OR "IoT")
AND ("agriculture" OR "agri-food" OR "agrifood" OR "food supply chain" OR "agricultural food supply chain")
AND ("food quality" OR "food safety" OR "cold chain" OR "postharvest" OR "traceability" OR "spoilage" OR "storage" OR "shelf-life" OR "contamination")

Scopus adaptation: The core Boolean string was applied using the TITLE-ABS-KEY field.

Web of Science adaptation: The core Boolean string was applied using the TS= field code.

Google Scholar adaptation: An equivalent free-text query was entered without Scopus or Web of Science field tags. The query retained the IoT, agri-food supply chain, and outcome concept blocks. The first 100 relevance-ranked results were screened, and records judged to be potentially eligible were captured using the Zotero browser connector. The available fields included title, year, source, and URL; complete author-keyword, citation-count, and co-authorship metadata were not available for bibliometric export. The archived record does not retain the complete raw Google Scholar capture count or its exact overlap with Scopus and Web of Science; only five records in the consolidated pool were identifiable as originating solely from Google Scholar or citation chasing.

A.3. Bibliometric analysis protocol

Purpose: To map publication growth, geographic participation, author-keyword relationships, and thematic structure in IoT-enabled AFSC research from 2015 to 2025 and to contextualise the SLR findings (RQ1).

Parameter	Specification
Records in record-level bibliometric corpus	625 Scopus and Web of Science records with complete structured metadata, retained before cross-source deduplication for descriptive mapping
Records excluded from corpus	Five records identifiable only through Google Scholar or citation chasing and lacking complete indexed bibliometric metadata
Export format	RIS for VOSviewer and plain CSV for Bibliometrix
Software platforms	VOSviewer and the Bibliometrix R package
Term harmonisation	Spelling variants, plural forms, hyphenated variants, and unambiguous synonyms were consolidated before analysis
Co-authorship analysis	Country-level co-authorship mapping after sparse nodes were filtered for interpretability; the exact numerical threshold was not retained
Keyword analysis	Author-keyword co-occurrence and thematic mapping after sparse terms were filtered; exact occurrence and clustering settings were not retained
Bibliometrix analysis	Annual publication output, source and author rankings, three-field relationships, and thematic structure generated with standard package functions
Interpretation	Descriptive record-level mapping only; outputs were not interpreted as counts of unique studies, causal evidence, or inferential evidence
Outputs	Figure 1, annual publication output; Figure 2, three-field plot; Figure 3, strategic thematic map

A.4. Systematic literature review (SLR) protocol

Purpose: To synthesise quantified outcome evidence for IoT interventions across seven AFSC stages, identify stage-wise evidence asymmetry, and propose stage-appropriate performance metrics (RQ2 and RQ3), following the PRISMA 2020 guidance.

PICO element	**Eligibility specification**
Population	Stakeholders or settings across seven AFSC stages: pre-production, production, processing, storage, transportation, distribution and retail, and consumption
Intervention	IoT technologies used to monitor, control, or optimise food quality, safety, traceability, resource use, or related AFSC processes
Comparator	Conventional or standard practice without IoT where available; non-comparative studies were eligible when they reported relevant quantitative outcomes
Outcomes	Quantitative measures of food quality, safety, traceability, resource efficiency, yield, spoilage, shelf-life, or related operational performance
SLR parameter	**Specification**
Records screened	392 after removal of 238 duplicates from 630 retrieved records
Reports sought and assessed	84 reports sought; 82 assessed in full text because two could not be retrieved
Studies included	68: 8 pre-production, 21 production, 7 processing, 8 storage, 9 transportation, 8 distribution and retail, and 7 consumption
Screening agreement	Cohen's $\kappa = 0.81$, indicating strong inter-rater agreement
Quality appraisal	JBI critical appraisal checklists appropriate to each study design; disagreements resolved through discussion
Synthesis method	Narrative synthesis by AFSC stage; meta-analysis was not conducted because of design and outcome heterogeneity
Sensitivity analysis	Nineteen low-quality studies were excluded; evidence-strength conclusions did not change (Appendix C)

A.5. Exclusion criteria

The following record types were excluded: conceptual publications, narrative reviews without primary data, editorials, opinion pieces, studies conducted outside agricultural supply chains, and papers reporting only qualitative or socioeconomic outcomes without relevant quantitative data on food quality, safety, traceability, resource use, yield, spoilage, or shelf-life.

A.6. Count reconciliation

Table A.6 reconciles the bibliometric and systematic review counts reported in the abstract, the methods section, Figure 4, the results, and the appendices

Processing stage	Count	Reconciliation note
Retrieved records in the shared record-level pool	630	Consolidated records retained after database searching, source-level screening, and citation chasing; complete raw source-specific counts and the exact allocation of overlapping records were not retained
Records in the record-level bibliometric corpus	625	625 Scopus and Web of Science records with complete structured metadata, retained before cross-source deduplication for descriptive mapping
Records excluded from bibliometric analysis	5	Five records identifiable only through Google Scholar or citation chasing and lacking complete indexed bibliometric metadata
Duplicates removed before SLR screening	238	Removed only when constructing the deduplicated SLR screening pool
Records screened by title and abstract	392	630 retrieved records minus 238 duplicate records
Records excluded during title and abstract screening	308	392 records screened minus 84 reports sought
Reports sought for retrieval	84	Potentially eligible reports after title and abstract screening
Reports not retrieved	2	Full text was unavailable
Reports assessed in full text	82	84 reports sought minus two not retrieved
Reports excluded after full-text assessment	14	No relevant quantitative outcome (n = 8); outside an agricultural supply-chain context (n = 4); duplicate reporting of the same study (n = 2)
Studies included in the systematic review	68	82 reports assessed minus 14 excluded; stage totals sum to 68

Appendix B: Data extraction framework and quality appraisal documentation

This appendix documents the extraction variables and coding guidance used for the 68 included studies, the JBI quality appraisal domains applied, and representative extraction records for the studies discussed in the manuscript. The complete extraction matrix and study-level appraisal records are available from the corresponding author, in accordance with the data availability statement.

B.1. Extraction variables and coding guidance

Variable	Definition	Coding guidance
Study identifier	Author(s) and year	First-author surname and year, for example, Sachin 2023
AFSC stage	Primary AFSC stage addressed	Pre-production, production, processing, storage, transportation, distribution and retail, or consumption
Country/region	Country(ies) of study conduct	ISO country name; code as "multi-country" when more than one country was included
IoT technology	Primary IoT technology	Recorded as free text, then classified as: sensor or wireless sensor network (WSN), RFID or QR, GPS, smart device, platform or cloud, or hybrid
Study design	Research design	Controlled trial, quasi-experimental, before-and-after, observational, case study, simulation, prototype, or review
Comparator	Baseline or control condition	Describe the baseline or code "none stated"
Primary outcome	Main quantitative outcome	Record the principal quantitative outcome and unit, for example, percentage yield change or excursion frequency
Outcome value	Reported result	Record the exact value or range and specify whether a percentage is relative or absolute
Sample size	Study scope	Record the unit of analysis, such as hectares, plots, sensors, animals, or containers
Duration	Observation/trial length	Record duration in days, seasons, or years; code "not stated" when unavailable
Statistical test	Inferential method	Record the inferential test; code "none" for descriptive analysis and "NR" when not reported
Significance	Statistical significance	Record the p value or significance level; code "NR" when not reported
JBI quality rating	Appraisal outcome	High, moderate, or low, based on reviewer consensus
JBI domains failed	Checklist items not met or unclear	List checklist domains rated no or unclear; code "none" for high-quality studies
Excluded in sensitivity	Whether excluded in sensitivity analysis	Yes or no

B.2. JBI appraisal domains and failure patterns

Quality was appraised using the JBI critical appraisal checklists appropriate for each study design. The three domains marked with an asterisk were the most frequent reasons for classifying studies as low quality in the sensitivity analysis.

#	JBI domain	Typical deficiency in this corpus	Number of studies with the deficiency
1	Clear inclusion criteria and setting	Eligibility criteria or setting not stated clearly in some small pilots	Not separately reported
2	Valid measurement of condition	Sensor calibration procedures incompletely described	Not separately reported
3	Valid measurement of intervention	IoT intervention specifications incomplete	Not separately reported
4*	Comparable groups / comparator defined	Formal comparator or control condition absent	14
5	Complete follow-up	Observation period too short or follow-up incomplete	Not separately reported
6*	Outcomes measured in same way for all	Outcome measure undefined or not standardised	11
7	Reliable measurement	Sensor drift or measurement reliability not addressed	Not separately reported
8	Appropriate statistical analysis	Descriptive analysis only or inferential method not reported	Not separately reported
9*	Participant/setting characteristics described	Participants or setting described inadequately	9

An asterisk identifies the domains most frequently associated with low-quality classification. Counts overlap because a study could have deficiencies in more than one domain; no stage-specific distribution is inferred from these totals.

B.3. Representative study-level extraction records

Table B.3 presents representative extraction records for empirical studies discussed in the manuscript. Contextual reviews used only for literature positioning are excluded from this table. The table does not replace the complete extraction matrix, which is available from the corresponding author upon reasonable request

Reference	Study	Stage	Country	IoT technology	Design	Comparator	Primary outcome	Reported result	JBI rating
[36]	Cil et al., 2022	Transportation	Turkey	IoT temperature sensors (container port)	Observational deployment	Periodic manual inspection	Detection delay and excursion-alert latency	No pooled estimate	Moderate
[51]	Afreen and Bajwa, 2021	Storage	Pakistan	IoT monitoring and notification system (cold storage)	Observational deployment	Pre-deployment baseline	Frequency and duration of off-temperature events	Reduced; no pooled percentage	Moderate
[43]	Venkatesh et al., 2023	Production	India	Wireless smart sprinkler irrigation system	Prototype design and implementation	No quantified comparator	System functionality and water-use rationale	Technical functionality described; no quantified comparative yield effect reported	Limited
[47]	Sachin et al., 2023	Production	India	Sensor-based precision nutrient and irrigation	Field trial	Conventional scheduling	Soybean yield and water productivity	Grain yield was 23.1–29.1% higher under sprinkler irrigation at 80% crop evapotranspiration than under flood irrigation across two study years; water-productivity measures also improved	High

Reference	Study	Stage	Country	IoT technology	Design	Comparator	Primary outcome	Reported result	JBI rating
[88]	Ramanathan et al., 2022	Distribution and retail	United Kingdom	Digital-technology process monitoring	Case study	Pre-intervention baseline	Food-waste reduction	Effect not disaggregated by technology type	Moderate

Appendix C: Sensitivity analysis results

This appendix reports the verified sensitivity analysis based on the JBI quality appraisal. The results are presented as aggregate counts and evidence strength classifications because stage-specific exclusion counts were not retained.

C.1. Rationale

Studies classified as low quality were excluded from the base corpus of 68 studies to assess whether the stage-level conclusions depended on the weaker evidence.

C.2. JBI domains driving low-quality exclusion

The three JBI domains most frequently associated with exclusion were the absence of a formal comparator or control condition (n = 14), failure to define or standardise the outcome measure (n = 11), and inadequate description of participants or settings (n = 9). These counts overlap because individual studies could have deficiencies in more than one domain.

The bibliometric component was not subjected to sensitivity analysis of keyword-frequency, publication-count, co-occurrence, or clustering thresholds.

C.3. Sensitivity analysis results by AFSC stage

AFSC stage	Base evidence strength	Restricted evidence strength	Conclusion changed?	Interpretation	Count basis
Pre-production (input procurement)	Limited	Limited	No	Input-related outcome evidence remained sparse	Stage count not reported
Production	High	High	No	Evidence remained strongest and most consistently quantified	Stage count not reported
Processing	Limited	Limited	No	Evidence remained pilot- and process-specific	Stage count not reported
Storage	Moderate	Moderate	No	Condition-monitoring evidence remained consistent	Stage count not reported
Transportation	Moderate	Moderate	No	Cold-chain telemetry evidence remained consistent	Stage count not reported
Distribution and retail	Limited	Limited	No	Operational impact evidence remained case-based and insufficiently standardised	Stage count not reported
Consumption	Limited	Limited	No	Field-tested food-security outcomes remained scarce	Stage count not reported
Overall	68 studies	49 studies	No	The main stage-wise asymmetry was unchanged	Nineteen exclusions verified in aggregate

The verified aggregate counts were 68 studies in the base corpus, 19 low-quality exclusions, and 49 studies in the restricted corpus.

C.4. Effect on conclusions

After excluding the 19 low-quality studies, the evidence pattern remained unchanged. Production retained high evidence strength; storage and transportation retained moderate evidence strength; and evidence strength remained limited at the pre-production, processing, distribution-and-retail, and consumption stages. Therefore, the principal stage-wise asymmetry was not driven by the low-quality subset.

C.5. Limitation of sensitivity analysis

The sensitivity analysis was limited to the SLR. Stage-specific exclusion counts are not reported because they were not retained in the appraisal summary; therefore, Table C.3 presents evidence strength classifications and verified aggregate counts only.