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The Security-by-Design Deficit: An Analysis of the Structural Disconnect in AI-Agriculture Adoption Research

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Abstract

Artificial intelligence (AI) is rapidly transforming agricultural research and practice, yet the structural organization of this knowledge base remains poorly understood. This study employs bibliometric analysis, specifically VOSviewer co-occurrence network analysis, to examine 711 peer-reviewed publications on AI-Agriculture adoption published between 2019 and 2025. Using the Louvain clustering algorithm, four thematic clusters are identified: a dominant Technical AI/ML Core, a Predictive Modeling and Environmental Forecasting cluster, a Precision Livestock Farming cluster, and a Socio-Organizational and Policy cluster. Findings reveal a field organized primarily around technical optimization, with governance, security, and privacy themes structurally marginalized. Only 57 papers (8% of the corpus) explicitly address cybersecurity or data privacy, and the term security is positioned within the socio-organizational cluster rather than integrated into technical development streams. This structural disconnect is characterized as a "security-by-design deficit," wherein cybersecurity is treated as an implementation concern rather than a core design requirement. These findings carry implications for aligning AI-Agriculture research trajectories with emerging responsible AI governance frameworks, including privacy-by-design and security-by-design principles. The study contributes empirical bibliometric evidence of this structural gap and offers a research agenda for building more secure, trustworthy, and governance-aligned AI systems in agriculture.

Keywords: artificial intelligence, agriculture, AI adoption, cybersecurity, security-by-design

Introduction

Artificial intelligence (AI) has transformed agricultural research and practice. Advances in sensing, computing, and intelligent systems have accelerated smart agriculture adoption. Technologies such as IoT, AI, big data analytics (BDA), blockchain, unmanned aerial vehicles (UAVs), and remote sensing (RS) enable large-scale remote monitoring, real-time control, and advanced data-driven analysis (El-Gayar & Ofori, 2021; Kerkech et al., 2020; Nan et al., 2025; Wu et al., 2025). Yet, agriculture and the global food system stand at a critical crossroads, facing unprecedented pressure from rapid population growth and rising food demand. With the United Nations projecting a global population of 10 billion by 2050, necessitating a 70% increase in food production (El-Gayar & Ofori, 2021; Wu et al., 2025), the industry faces an urgent need to enhance productivity. Despite these advances, significant adoption challenges remain.

Approximately 80% of global agricultural operators are smallholders, creating substantial barriers to AI adoption (Wu et al., 2025). Economic constraints, limited technical literacy, and inadequate infrastructure restrict technology access. Furthermore, a lack of awareness regarding sustainability outcomes complicates the transition to responsible systems (Shamsuddoha & Nasir, 2025). This presents a tension between AI's transformative potential and the structural challenges to inclusive adoption in food production systems.

Consequently, Information Systems (IS) literature is increasingly finding ways to improve AI–Agriculture adoption. The accelerated growth of this research domain calls for mapping its knowledge structure to identify research gaps and guide inquiry (Cubric, 2020; Díaz et al., 2025). From an IS perspective, this evolution extends beyond algorithmic performance to include governance, security, and privacy considerations that shape responsible system deployment. Frameworks for trustworthy AI development, including the NIST AI Risk Management Framework (Tabassi, 2023), emphasize embedding privacy-by-design and security-by-design throughout system lifecycles. However, whether AI-Agriculture research trajectories align with these design principles remains unclear (Sethibe, 2019). Despite numerous adoption-focused studies and literature reviews, the AI-Agriculture field lacks a holistic, data-driven understanding of its intellectual structure, specifically, which themes dominate the knowledge base and which remain weakly integrated (Saidu et al., 2025). This fragmentation risks fostering technological solutionism, where sophisticated algorithms are developed in isolation from the governance and accountability requirements necessary for secure and trustworthy adoption (Trabelsi et al., 2023). Understanding whether research trajectories align with emerging expectations for responsible AI design is essential for assessing the field's capacity to operationalize security and privacy principles into deployed systems (Al-Thani et al., 2025).

Existing primary studies and reviews focus on narrow applications or predefined boundaries, neglecting cross-domain relationships, structural imbalances, and the positioning of socio-technical concerns like governance and security (Manetti et al., 2025; Montalvo et al., 2025; Paul & Machavaram, 2025). This gap represents a lack of field-level structural insight rather than volume. This study investigates:

- RQ1: What are the dominant thematic clusters in AI-Agriculture, and how does the network structure reveal the relationship between technical innovation and socio-organizational dimensions?
- RQ2: To what extent are cybersecurity and privacy integrated into the core AI-agriculture adoption research agenda?

Methodology

This study employed a bibliometric research design to examine global AI agriculture adoption research trends. This approach is well suited for mapping knowledge structures and identifying thematic patterns in rapidly evolving research domains (Donthu et al., 2021; Zupic & Čater, 2015). We captured research trends between 2019 and 2025, a timeframe deliberately selected to target the period when deep learning methods became the dominant paradigm in agricultural AI and adoption emerged as a distinct research framing. This window also coincides with the rise of responsible-AI governance instruments, such as the NIST AI Risk Management Framework (Tabassi, 2023), against which we assess the field's alignment. The concentration of the corpus in 2024–2025 (64.5%) confirms that this window captures the active research front rather than a historical tail.

Data Collection

Publications were retrieved from six major academic databases: ABI/INFORM, ACM Digital Library, AGRICOLA, Academic Search Premier, IEEE Xplore, and Web of Science. A structured search strategy was developed around technology, domain, and adoption concepts using the query: "artificial intelligence" AND ("agri*" OR "farm*") AND "adopt*". Searches were limited to peer-reviewed journal articles, conference proceedings, and book chapters. Records were merged, de-duplicated, and screened for

relevance to AI-Agriculture adoption. The final dataset comprised **711 unique publications** from Jan 2019 to Dec 2025, with the majority concentrated in 2024-2025 (n=459, 64.5%). Identical Boolean logic was applied across all six databases, adapted to each platform's native syntax. Screening proceeded in three stages: deduplication of records, title-and-abstract relevance screening against the AI-Agriculture adoption scope, and full-text eligibility confirmation, with borderline cases resolved by consensus.

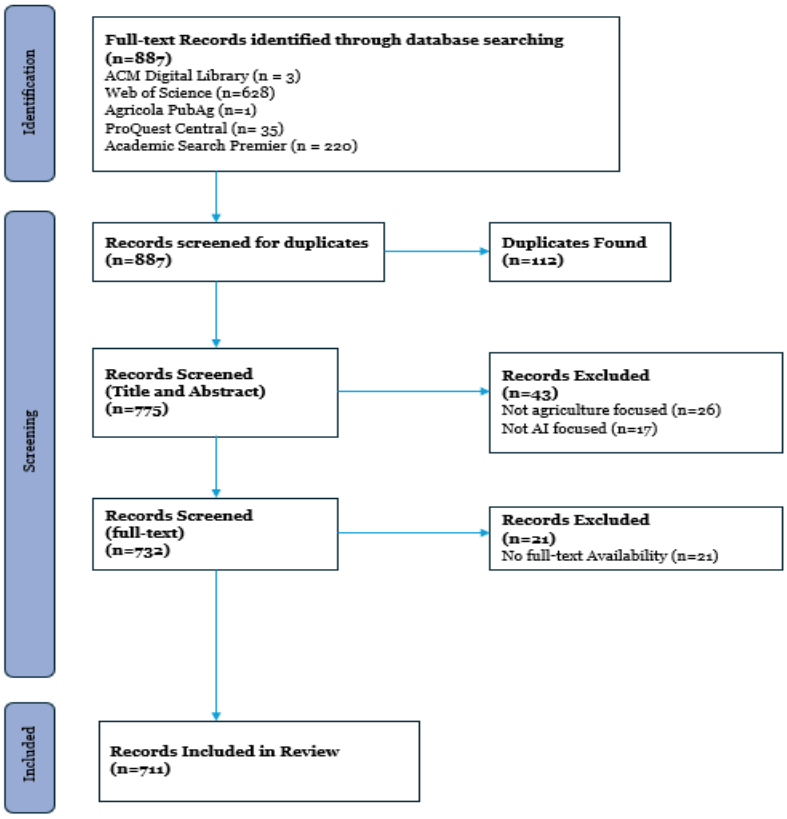


Figure 1: PRISMA Flowchart

Bibliometric Analysis

VOSviewer co-occurrence network analysis extracted terms from titles and abstracts using full counting with a minimum occurrence threshold of 9 to identify significant terms. This threshold ensured the network visualization remained legible and focused on core themes, consistent with prior bibliometric mapping studies. The Louvain algorithm identified four thematic clusters, visualized via distance-based mapping where proximity indicates relatedness. Following (Cobo et al., 2011), clusters were interpreted using strategic diagram logic based on centrality and density. It should be noted that VOSviewer clusters terms rather than documents; individual papers may contain keywords belonging to multiple thematic clusters. Consequently, when reporting cluster coverage, we indicate the number and percentage of papers containing at least one term from each cluster.

To enhance methodological rigor, multiple disciplinary databases were used, and standardized data cleaning procedures were applied. However, bibliometric analysis captures structural patterns in language usage rather than theoretical depth or causal relationships. Accordingly, findings are interpreted as indicators of thematic organization within the literature.

Results & Discussion

The analysis reveals a highly structured yet uneven intellectual landscape within AI–Agriculture adoption research. As shown in Figure 2, the network organizes into four primary clusters differing in size, density, and structural centrality. Because papers may engage with terms from multiple clusters, the coverage percentages reported below reflect thematic reach rather than exclusive membership, since VOSviewer clusters terms rather than documents.

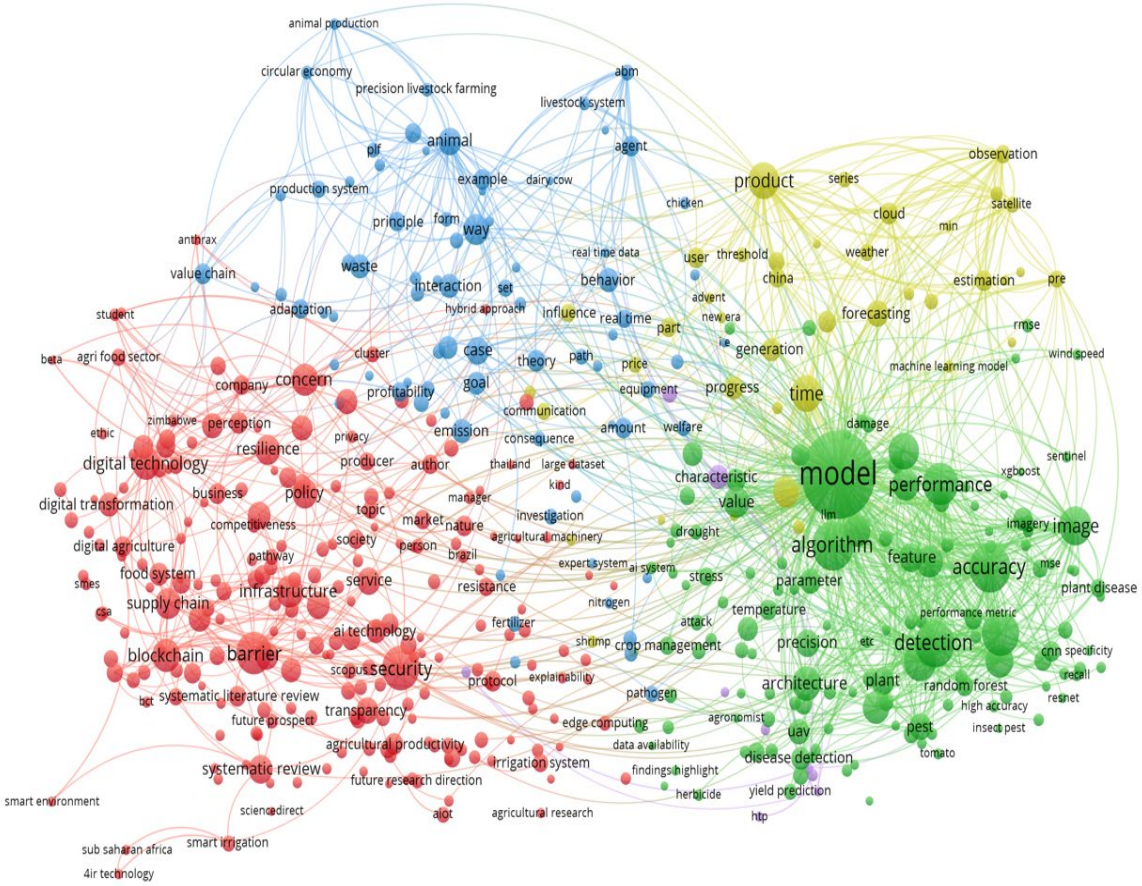


Figure 2: Co-Occurrence Network of AI–Agriculture Research Themes (2019–2025)

The Green Cluster: Technical AI/ML Core, centered on AI models, performance metrics, and computer vision applications, occupies the central position of the network and represents the dominant methodological foundation of the field. The Yellow Cluster: Predictive Modeling and Environmental Forecasting forms an infrastructural bridging layer, linking remote sensing, climate data, and forecasting models to downstream agricultural applications. The Blue Cluster: Precision Livestock Farming and Systems Ecology represents a domain-specific application stream focused on animal production systems, behavioral monitoring, and circular economy perspectives, and it appears rather weakly integrated with the technical core. Finally, the Red Cluster: Socio-Organizational and Policy captures adoption-related themes including governance, barriers, supply chain integration, and trust, and is positioned more peripherally, indicating limited structural integration with dominant technical research streams.

Uncovering Dominant Themes and their Structural Organization

Green Cluster: Technical AI/ML Core

This largest, densest component of the network, covering 611 papers (81.5% of the corpus), centers on terms including model, performance, accuracy, dataset, detection, image, feature, architecture, CNN, LSTM, precision, yield, pest, disease detection, weed detection, plant disease, and object detection. This cluster represents the field's methodological foundation. The prominence and centrality of performance-related keywords (e.g., model, accuracy, detection, algorithm) indicate that AI–Agriculture research remains heavily oriented toward optimization and prediction accuracy.

Representative work includes (Demilie, 2024) comparing deep learning architectures for plant disease classification, (Subramani et al., 2025) reviewing machine learning and deep learning techniques for poultry management, and (Virnodkar et al., 2020) providing a critical review of remote sensing and machine learning for determining crop water stress. As (Demilie, 2024) demonstrates, research in this cluster focuses primarily on optimizing algorithmic metrics, with convolutional neural networks (CNNs) achieving accuracy rates exceeding 95%.

Red Cluster: Socio-Organizational and Policy

The second-largest cluster (591 papers, 83.1%) comprises policy, barrier, security, blockchain, supply chain, digital technology, resilience, adoption, concern, SDGs, traceability, transparency, and agricultural food productivity. It addresses implementation challenges, governance frameworks, and development contexts. The network visualization further illustrates that security and privacy concepts are clustered within the socio-organizational domain and remain weakly connected to the dominant Technical AI/ML Core (Green) performance cluster. Key publications include (Virmani & Singh, 2024) analyzing barriers to blockchain adoption in agri-food supply chains, (Alexander et al., 2024) examining responsibility attribution challenges in building trust for AI-Agriculture technology, and (Moyo et al., 2025) investigating blockchain-IoT in Zimbabwe. The cluster exhibits strong geographic concentration on Global South contexts, reflecting recognition that adoption challenges are context-dependent (Farinha & Martins, 2025; Nawaz & Babar, 2025).

Blue Cluster: Precision Livestock Farming and Systems Ecology

This domain-specific cluster (124 papers, 17.4%) focuses on animal, livestock system, production system, circular economy, dairy sector, behavior, and animal production, appearing as an "island" with minimal linkage to security constructs.

Key works in this cluster include (Lima-Campêlo, 2024), (Shamsuddoha & Nasir, 2025) and (Jeong et al., 2022) on smart agriculture dairy practices, (Antognoli et al., 2025) on computer vision applications in dairy farm management, and (Das et al., 2023) who bridge this cluster to sustainability themes through AI-enabled circular economy perspectives in food grain supply chains.

Yellow Cluster: Predictive Modeling and Environmental Forecasting

Consisting of 367 papers (51.6%), this infrastructure cluster spans forecasting, time, weather, estimation, prediction model, satellite, sentinel, lidar, cloud, and vegetation index connecting remote sensing platforms to predictive modeling.

(Virnodkar et al., 2020) exemplifies this cluster's integration of remote sensing data with machine learning models for agricultural monitoring. (Kazancoglu et al., 2024) connect forecasting capabilities to climate-smart farming strategies, while (Ganeshkumar et al., 2023) examine how forecasting integrates across the agricultural value chain. The cluster structurally bridges technical methods and application domains.

Socio-Technical Interpretation of Thematic Clusters
Drawing on Socio-Technical Systems theory (Geels, 2004) and the distinction between hardware, software, and orgware (Klerkx et al., 2019), we categorized the four clusters into three dimensions:

- **Technical:** Functioning as motor themes (Cobo et al., 2011) driving field development, this dimension encompasses the AI/ML algorithms of the green cluster and the predictive elements of the yellow cluster. This aligns with the view that "Digital technologies are often analyzed as technical components (software/algorithms)." (Klerkx et al., 2019)

- **Infrastructural:** This dimension captures the sensing layer, specifically the remote sensing elements of the yellow cluster. "The 'Socio-Cyber-Physical' framework emphasizes the physical infrastructure (sensors, satellites) required for digital twins." (Rijswijk et al., 2021)

- **Socio-Organizational:** Serving as the bridge to implementation, this dimension includes the policies and barriers of the red cluster and the production systems of the blue cluster. Its framing is predominantly deficit-oriented (barriers, concerns, challenges) rather than enablement-focused, consistent with (Klerkx & Rose, 2020) call to address the social implications of Agriculture 4.0. "Successful innovation requires 'Orgware' (institutional conditions, policy and adoption)." (Klerkx & Rose, 2020; Leeuwis & Aarts, 2010)

Table 1: Research Clusters and Their Roles in AI–Agriculture Adoption Ecosystems

	Clusters	Bridging Terms
Technical: Hardware / Software	AI/ML Core (Green), Forecasting (Yellow)	model, performance, prediction model
Infrastructural: Physical / Infrastructure	Remote Sensing (Yellow)	satellite, sensor, real-time monitoring, IoT
Socio-Organizational: Orgware / Social System	Policy/Barriers (Red), Production Systems (Blue)	policy, barrier, adoption, farmer, behavior

Are We Secure? The Footprint of Cybersecurity, Privacy, and Data Security in AI-Agriculture
Within the adoption-focused literature mapped here, cybersecurity, data security, and privacy concerns occupy a structurally marginalized position. Only 57 papers (8% of the corpus) explicitly address these themes. Because our search focused specifically on adoption literature, deliberately excluding stand-alone technical security papers, this 8% could be interpreted as a lower bound rather than the current industry-wide benchmark. To evaluate this gap, we operationalize security-by-design as the embedding of confidentiality, integrity, and availability protections from a system's inception, consistent with the NIST AI Risk Management Framework (Tabassi, 2023). Structurally, the term security is located within the socio-organizational (red) cluster rather than integrated into the technical (green) or infrastructural (yellow) clusters where AI systems and IoT devices are developed.

Network Position Analysis
In the VOSviewer visualization, security appears adjacent to blockchain, barrier, supply chain, and traceability, indicating that security is conceptualized primarily in relation to supply chain integrity and implementation barriers rather than as a core design requirement for AI systems. The term privacy does not appear as a distinctively visible node in the network suggesting minimal research attention in AI-Agriculture adoption. More broadly, no governance-related concepts emerge as central network hubs,

indicating that privacy, trust, and accountability are not serving as organizing principles within the current research structure.

This positioning aligns with (Alahe et al., 2024) observation that until recently, agriculture received extraordinarily little attention in terms of cybersecurity, and cyber defense practices were often neglected within the sector. Security is framed as an implementation challenge, not a system design principle. The structural marginalization visible in our network analysis provides empirical validation of this assessment.

Security-Focused Publications

Despite overall weak integration, some papers directly address security concerns, though they map unevenly across the confidentiality, integrity and availability spectrum:

- **Cybersecurity infrastructure:** (Javeed et al., 2024) presents an intrusion detection system for edge-envisioned smart agriculture in extreme environments, primarily addressing system availability and integrity. (Gao et al., 2024) provide a position paper on security threats to agricultural AI in Computers & Electronics in Agriculture, representing one of the few papers directly situating security within the technical domain.

- **Privacy frameworks:** (Rahaman et al., 2024) addresses privacy-centric AI and IoT solutions for smart rural farm monitoring, focusing on data confidentiality. (Chowdhury & Edet, 2025) propose frameworks for responsible AI-driven agri-food innovation in Ontario with explicit attention to privacy concerns.

- **Blockchain for security:** (Moyo et al., 2025) examines blockchain-IoT integration for supply chain security among Zimbabwean farmers. However, blockchain appears more frequently in relation to traceability (integrity**)** than security. This suggest**s** a framing oriented toward market access rather than threat mitigation.

- **Adoption barriers:** (Uddin et al., 2024) examine legal and ethical aspects of AI deployment, including privacy implications. These papers frame security as an implementation challenge rather than a research priority.

Integration Strength Assessment

Cybersecurity themes exhibit weak integration with other research themes. This weak integration of security themes represents a significant gap given the vulnerability of IoT-enabled agricultural systems. As (Campoverde-Molina & Luján-Mora, 2025) note in their systematic literature review, there exists a lack of comprehensive review addressing cybersecurity in smart agriculture, and our findings confirm that this gap extends to the broader AI-Agriculture research base, as evidenced by the table below:

Table 2: Structural Integration of Cybersecurity and Data Privacy in AI–Agriculture Research

Integration Metric	Level	Evidence
Corpus coverage	Very Weak	57/711 papers (8%)
Cluster position	Peripheral	Located in Red cluster (barriers), not Green (technical)
Technical core linkage	Weak	Not linked to model, architecture, dataset terms
IoT infrastructure linkage	Very Weak	Security not connected to sensor, IoT, satellite terms
Conceptual framing	Deficit-oriented	Framed as barrier/concern, not design requirement

Conclusion

This bibliometric analysis reveals that recent AI-Agriculture adoption research can be organized along four thematic clusters, with a knowledge base oriented primarily around technical optimization (green), supported by infrastructure (yellow) and domain applications (blue), while socio-organizational and policy-oriented considerations (red), which constitutes security and governance terms, occupy a structurally peripheral position, weakly linked to the technical core. Because VOSviewer clusters terms rather than documents, individual papers routinely draw on vocabulary from several clusters. The resulting overlap in cluster coverage is therefore expected and does not contradict this peripherality, which is a property of the term co-occurrence network rather than of mutually exclusive document sets. This peripheral positioning of socio-technical terms reflects what (R. Veraart & Blok, 2021b; R. C. Veraart & Blok, 2021a) characterize as a techno-optimist orientation: it treats technological innovation as a standalone solution, prioritizing algorithmic performance while treating socio-technical integration as a peripheral concern. Additionally, the positioning of human agency and governance themes within the barrier-focused socio-organizational cluster, rather than integrated within technical development, suggests a linear technology transfer model wherein social considerations are addressed post-hoc. This finding aligns with (Benos et al., 2021) observation that agricultural AI research emphasizes CNN/ANN performance metrics while underemphasizing deployment contexts.

Research Gaps

Three critical gaps emerge from this analysis:

- **Security-by-design deficit:** Cybersecurity is not currently viewed as a primary factor in the adoption of agricultural AI. It is structurally disconnected from technical AI/ML development, appearing as an implementation concern rather than a design requirement. This mirrors (Gupta et al., 2020) finding that smart farm devices are not built with security as a concern.
- **Trust infrastructure underdevelopment:** Despite growing recognition of trust as critical for adoption (Alexander et al., 2024; Gardezi et al., 2024), explainability and trust terms remain peripheral in the network, suggesting insufficient research attention.
- **Governance-technology disconnect:** Policy and regulatory themes connect weakly to technical development, limiting the field's capacity for responsible innovation as advocated by (Van Der Burg et al., 2019).

Taken together, these gaps are particularly consequential given the growing emphasis in AI governance on embedding privacy-by-design, security-by-design, and accountability principles throughout system development (Chowdhury & Edet, 2025; Uddin et al., 2024) suggesting a potential misalignment between current AI–Agriculture research and emerging principles for responsible AI governance.

Contributions and Limitations

This study offers two main contributions to IS governance. First, it provides empirical bibliometric evidence that cybersecurity and privacy remain structurally peripheral within AI–Agriculture adoption research. Second, by introducing the concept of a "security-by-design deficit," this work reframes security as a systemic design challenge that requires alignment between technical innovation and governance requirements. Framed more pointedly, the study's central contribution is methodological: it demonstrates how adoption- and management-framed research systematically externalizes security, treating it as an implementation niche rather than an integral design concern, and it shows how a term co-occurrence lens can surface that externalization. Regardless, there are some challenges to study. The corpus scope (711 papers, 2019-2025), which may not capture the full breadth of AI-Agriculture research, and term co-occurrence analysis captures explicit linguistic patterns but may miss implicit thematic connections. The analysis is also a cross-sectional snapshot of the 2019–2025 corpus and does not trace whether security attention is increasing over time, and it includes no cross-domain benchmark (e.g., security-term frequency in medical, autonomous-vehicle, or smart-city AI); longitudinal trend analysis and cross-domain benchmarking are accordingly important directions for future work. In addition, our search query required the term "adopt*" to isolate adoption-focused literature. This likely excluded a segment of technical engineering literature, such as papers focused on cryptographic protocols or intrusion detection that do not discuss adoption. Thus, our finding that cybersecurity is structurally marginalized should be interpreted within the context of adoption and management literature. This exclusion, however, reinforces our core argument: cybersecurity is treated as a specialized technical niche rather than as an integral component of the general discourse on AI implementation in agriculture.

Implications for Research

Our findings have implications for research agenda-setting: addressing the security-by-design deficit, strengthening trust connections to technical development, and integrating governance considerations earlier in the research process represent priorities for building more robust and responsible AI-enabled agricultural systems. For practitioners, the structural disconnect between infrastructure and security themes suggests that AgTech developers should embed privacy requirements during infrastructure deployment rather than treating data protection as a downstream concern.

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