

Artificial intelligence for palm oil supply chain traceability: a review of tools, claims, and evidence

Abstract

Palm oil supply chain traceability has become increasingly important for transparency, sustainability commitments, and market compliance. Artificial intelligence (AI) has attracted growing attention as a potential enabler of traceability; however, the extent to which empirical evidence supports its reported capabilities remains insufficiently synthesised. This study identified and categorised AI tools applied across the palm oil supply chain, critically examined claims regarding their traceability and sustainability benefits, and assessed the evidence supporting those claims. A Systematic Literature Review was conducted in accordance with PRISMA 2020. A preliminary Scopus scoping query returned 383 records and was used only to refine the terminology; the formal final Boolean search yielded 104 records. After 11 records outside the 2021–2026 publication window and 72 thematically ineligible records were excluded, 21 scholarly publications were retained for qualitative synthesis. Data extraction, thematic synthesis, and a design-sensitive methodological-quality appraisal were undertaken. Six clusters were identified: AI- and blockchain-enabled traceability systems, AI-driven forecasting and decarbonisation, organisational readiness, Industry 4.0 technologies, precision agriculture, and spectroscopic authentication. The evidence shows credible capability at discrete traceability nodes, including plantation identification, product authentication, and emissions monitoring, but remains insufficient to establish fully integrated, end-to-end traceability. Future research should prioritise longitudinal, multi-stage, and cross-regional evaluations of scalable AI-enabled systems.

Keywords: artificial intelligence, palm oil, supply chain traceability, systematic literature review, sustainability

Special Issue - 2026

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Received: August 05, 2026 | **Published:** August 25, 2026

Introduction

Palm oil is among the most widely produced and traded vegetable oils in the global agricultural economy, underpinning food, cosmetic, and biofuel industries across developed and developing markets.¹ Its exceptional yield efficiency relative to other oil-bearing crops has positioned it as a strategically important commodity for major producing countries, particularly Indonesia and Malaysia, which together account for the overwhelming majority of global supply.² This economic significance, however, has been accompanied by sustained scrutiny regarding the environmental and social externalities associated with palm oil cultivation, including deforestation, peatland conversion, and biodiversity loss, concerns that have shaped an increasingly stringent global regulatory landscape.³ Regulatory instruments such as the European Union Deforestation Regulation and voluntary certification schemes including the Roundtable on Sustainable Palm Oil have sought to condition market access on demonstrable, verifiable compliance with deforestation-free and socially responsible production practices.⁴

At the core of these regulatory and market-based mechanisms lies a persistent operational challenge: tracing palm oil products from fresh fruit bunches harvested at plantation level through processing, refining, and international trade back to their point of origin with sufficient granularity and verifiability.⁵ Traceability is complicated by a highly fragmented upstream structure in which substantial production originates from independent smallholders whose plantations may be undocumented, geographically dispersed, and administratively invisible to downstream buyers and certifying bodies.⁶ This structural fragmentation limits the ability of paper-based documentation and periodic physical audits to maintain a continuous and independently verifiable chain of custody across commingled supply networks.⁷

In response to these limitations, artificial intelligence has been proposed and, in several cases, empirically applied as a technological enabler of palm oil traceability.⁸ Remote sensing and machine-learning approaches have supported high-resolution plantation mapping and the spatial identification of smallholder holdings.^{9,10} Product-origin authentication has been investigated through Fourier transform infrared spectroscopy combined with discriminant modelling and through ¹H nuclear magnetic resonance spectroscopy combined with machine learning.^{11,12} At supply-chain level, blockchain and deep-learning architectures have also been applied to the tracking of greenhouse-gas emissions across a defined cradle-to-port palm oil chain.¹³ These developments form part of the broader transition from Industry 4.0 to Agriculture 4.0, in which AI, the Internet of Things, remote sensing, and distributed ledgers are reshaping how agri-commodity systems are monitored and governed.¹⁴

Despite this proliferation of technological proposals, a critical disjuncture appears to characterise the existing body of literature: claims regarding the traceability-enhancing potential of artificial intelligence are frequently advanced at a conceptual or aspirational level, while rigorous empirical evidence demonstrating that such technologies deliver measurable improvements in traceability outcomes, or translate into verifiable reductions in deforestation and non-compliance, remains comparatively scarce and unevenly distributed across the literature.¹⁵ Furthermore, a substantial proportion of artificial intelligence research within the oil palm sector has historically concentrated on precision agriculture applications, including yield prediction, disease detection, and fruit ripeness classification, rather than on traceability as a direct and primary research objective, suggesting a possible misalignment between where technological innovation has been most heavily invested and where the sector's most pressing accountability challenges reside.¹⁶

This pattern raises an important question regarding whether the technological narrative surrounding artificial intelligence and palm oil sustainability has outpaced the empirical evidence base required to substantiate it.¹⁷

Although several review articles have examined artificial intelligence applications in agriculture broadly, or Industry 4.0 adoption within the palm oil sector more generally, comparatively few studies have systematically synthesised the specific evidence base concerning artificial intelligence applications for palm oil supply chain traceability, disaggregating the tools employed, the claims advanced by their proponents, and the strength of evidence supporting those claims.¹⁸ This represents a meaningful gap in the literature, as policymakers, certification bodies, and industry stakeholders increasingly require a clear-eyed, evidence-based understanding of which artificial intelligence-enabled traceability mechanisms have demonstrated empirical efficacy, as opposed to those that remain largely theoretical or conceptual in nature, particularly as regulatory deadlines tied to deforestation-free sourcing commitments approach.¹⁹

Addressing this gap, the present study conducts a systematic literature review of scholarly publications indexed in Scopus, following the PRISMA 2020 reporting framework,²⁰ to map and critically synthesise evidence concerning the application of artificial intelligence to palm oil supply chain traceability. The review relies exclusively on previously published literature and does not use primary data collection methods such as field observation or focus-group discussion. It pursues three interrelated objectives: first, to identify and categorise the AI tools and technologies applied across different supply-chain segments; second, to critically examine claims regarding the traceability and sustainability benefits of those technologies; and third, to assess how far those claims are supported by empirical evidence, thereby distinguishing demonstrated capability from aspirational or conceptual assertion.

In pursuit of these objectives, this review addresses the following research question: to what extent does the empirical evidence generated by artificial intelligence applications in the palm oil sector substantiate the claims made regarding their capacity to deliver verifiable, end-to-end supply chain traceability, as distinct from their demonstrated contribution to adjacent precision agriculture and plantation management functions? This question is examined in detail in the Discussion section and subsequently addressed in the Conclusion, with the aim of providing a critically grounded and internationally relevant contribution to the ongoing discourse on technology-enabled sustainability governance in the global palm oil industry.

Literature review

This section establishes the theoretical foundation upon which the present review is constructed, situating artificial intelligence-enabled palm oil supply chain traceability within a broader architecture of interrelated theoretical perspectives. Five interconnected bodies of theory are examined in turn: the conceptual foundations of supply chain traceability, certification and institutional signalling theory, artificial intelligence and machine learning as technological enablers, blockchain as a complementary distributed ledger mechanism, and technology adoption frameworks that explain the translation, or lack thereof, of technical capability into verifiable outcomes. Together, these perspectives provide the conceptual scaffolding necessary to critically interpret the tools, claims, and evidence synthesised in the subsequent sections of this review.

Conceptual foundations of supply chain traceability

Supply chain traceability is conventionally defined as the capacity to identify, record, and retrieve the history, location, and application of a product as it moves through successive stages of production, processing, and distribution.²¹ Within agricultural commodity systems, traceability is typically conceptualised along two interrelated dimensions: tracking, which refers to the forward-facing capacity to follow a product from its point of origin toward the end consumer, and tracing, which refers to the backward-facing capacity to reconstruct a product's provenance from any point in the supply chain.²² This dual conceptualisation is particularly consequential for palm oil, given that fresh fruit bunches from geographically dispersed and often undocumented smallholder plantations are physically commingled with company-owned estate production once they reach the palm oil mill, thereby severing the direct link between a unit of crude palm oil and its plantation of origin unless deliberate segregation mechanisms are institutionalised at the point of collection.²³ Information asymmetry theory offers a useful lens for understanding why this loss of traceability constitutes a governance problem rather than a merely technical inconvenience: where downstream buyers, certifying bodies, and regulators cannot verify upstream production conditions, opportunistic actors face reduced incentives to comply with sustainability requirements, a dynamic that traceability systems are explicitly designed to mitigate by narrowing the information gap between supply chain actors.²⁴

Certification, signalling, and the institutional response to traceability gaps

In the absence of complete and continuously verifiable traceability, the palm oil industry has historically relied on third-party certification schemes, most notably the Roundtable on Sustainable Palm Oil, as an institutional substitute for direct observability.⁷ Signalling theory provides a coherent basis for interpreting certification because buyers and consumers cannot directly observe upstream production practices; certification therefore acts as a costly signal of compliance that can differentiate producers in markets characterised by asymmetric information.²⁵ Institutional theory further suggests that certification may also be adopted to conform to prevailing industry norms and maintain legitimacy, a dynamic that helps explain evidence that certified status does not invariably correspond with statistically significant reductions in deforestation.²⁶ This tension between certification as substantive verification and certification as legitimacy-conferring procedure underscores the need to determine whether emerging technologies strengthen the evidentiary substance of certification or simply add another layer of assurance.²⁷

Artificial intelligence and machine learning as technological enablers

Artificial intelligence, encompassing machine learning and deep learning, can support traceability through several technically distinct pathways rather than through a single unified mechanism.⁸ AI-assisted spatial systems can identify the position, area, and regulatory suitability of smallholder plantations, thereby strengthening the plantation-registration layer on which upstream provenance depends.¹⁰ Ensemble algorithms including Random Forest, Gradient Boosting, and XGBoost have also been applied to multi-sensor satellite indices for concession-scale carbon-stock estimation, although this verifies biophysical conditions rather than transaction-level chain of custody.²⁸ Time-series generative adversarial networks have been used to forecast palm oil trade demand and connect those forecasts with a

green supply-chain sustainability index, illustrating a predictive rather than documentary contribution to traceability.²⁹ At product level, Fourier transform infrared spectroscopy with discriminant analysis has authenticated geographical and temporal origin, whereas ¹H nuclear magnetic resonance spectroscopy with machine learning has discriminated crude palm oil origin and composition.^{11,12} These applications confirm that AI contributes at different points and levels of granularity within the supply chain, while their integration into a continuous provenance architecture remains a separate challenge.³⁰

Blockchain and the convergence of distributed ledger technology with artificial intelligence

Alongside artificial intelligence, blockchain technology has been theorised as a structurally distinct but complementary mechanism for supply chain traceability, owing to its capacity to create immutable, decentralised, and cryptographically verifiable records of transactions among multiple, potentially mutually distrustful supply chain actors.³¹ When integrated with smart contract architectures, blockchain systems can automate the recording and verification of supply chain events without reliance on a single trusted intermediary, a property considered particularly valuable in agricultural commodity systems characterised by numerous smallholder actors and limited institutional trust.³² Recent literature has begun to examine the convergence of blockchain and artificial intelligence, wherein predictive models generate the underlying data, such as emissions estimates or sustainability scores, that are subsequently recorded and verified through blockchain infrastructure, suggesting a hybridised technological architecture in which the two technologies perform complementary rather than substitutable functions.³³ Nonetheless, the diffusion of innovation theory suggests that the rate and extent of blockchain adoption within any given industry context is influenced not only by the technology's relative advantage but also by its compatibility with existing organisational routines, its perceived complexity, and the observability of its benefits to potential adopters, factors that have been found to significantly shape blockchain adoption readiness within the palm oil industry specifically.³⁴

Theoretical linkages between technology adoption and verifiable traceability outcomes

A recurring theme in the literature is the distinction between technological capability and organisational adoption. The Technology–Organisation–Environment framework locates adoption within the interaction of technological characteristics, organisational resources, and external pressures,³⁵ whereas the Technology Acceptance Model emphasises perceived usefulness and perceived ease of use as determinants of individual acceptance.³⁶ Applied to the palm oil sector, these perspectives suggest that technically validated AI or blockchain tools may still fail to diffuse where organisational readiness, financial capacity, skills, or infrastructure are inadequate, a pattern reflected in empirical work on blockchain-readiness factors in the industry.³⁷ The persistence of a traceability evidence gap may therefore reflect not only the maturity of particular tools but also the institutional incentives and implementation capacity that determine whether those tools are used at operational scale.³⁸

Taken together, the theoretical and empirical literature reviewed in this section indicates that supply chain traceability, certification and signalling theory, artificial intelligence and machine learning, blockchain-based distributed ledgers, and technology adoption frameworks constitute an interconnected theoretical architecture within

which the present review's central inquiry is situated. Traceability theory establishes why verifiable provenance matters; signalling and institutional theory explain the emergence of certification as an imperfect substitute for direct observability; artificial intelligence and blockchain represent the principal technological instruments proposed to strengthen this verificatory capacity; and technology adoption frameworks explain why the translation of technical capability into actual, sector-wide traceability outcomes remains uneven. This theoretical synthesis provides the conceptual foundation upon which the subsequent systematic review of tools, claims, and evidence is constructed.

Methods

This study employs a Systematic Literature Review approach reported in accordance with PRISMA 2020 to make the identification, screening, eligibility, and inclusion process transparent and reproducible.²⁰ The formal review focused on scholarly publications indexed in Scopus that were published from 2021 through 2026 and addressed AI, machine learning, deep learning, blockchain-integrated analytics, remote sensing, or spectroscopic-AI techniques in relation to the palm oil sector. To be eligible, a publication had to provide a direct traceability contribution or a clearly stated adjacent contribution to provenance, transparency, deforestation verification, emissions accounting, organisational adoption, or product authentication. Items were excluded when they fell outside the publication window, did not concern palm oil or oil palm, lacked a relevant digital or AI component, or did not contribute to the review question. Journal articles, conference proceedings, scholarly book chapters, and review publications were retained where they met these criteria; their differing evidentiary roles were subsequently addressed through structured quality appraisal. Background sources used only for theory or contextual framing were not counted among the twenty-one included publications and were not used as direct evidence in the thematic synthesis.

A preliminary Scopus scoping query using digital AND palm oil returned 383 records. This broad query was used only to test vocabulary and refine the final search strategy; it was not treated as the formal identification set, and the 279-record difference between the scoping and final searches was therefore not labelled as duplicates or screening exclusions. The formal PRISMA identification stage began with the final Boolean search: (“artificial intelligence” OR AI OR “machine learning” OR “deep learning”) AND (“palm oil” OR “oil palm”) AND (“supply chain” OR “supply chain management” OR traceability OR tracing OR provenance OR transparency OR blockchain OR sustainability). Applied in Scopus, this final search returned 104 records.

The 104 formally identified records were first restricted to the 2021–2026 publication window, which excluded 11 records and left 93 for screening. Titles and abstracts were then assessed against the eligibility criteria, with full text consulted where the abstract was insufficient to determine relevance. All 93 reports were retrievable; no item was classified as a report not retrieved. Seventy-two records were excluded because they did not establish a sufficiently direct relationship between the relevant technology, the palm oil sector, and the review's traceability or sustainability-accountability focus. The remaining 21 publications were included in qualitative synthesis. Figure 1 reports these quantities using labels that correspond exactly to the narrative sequence.

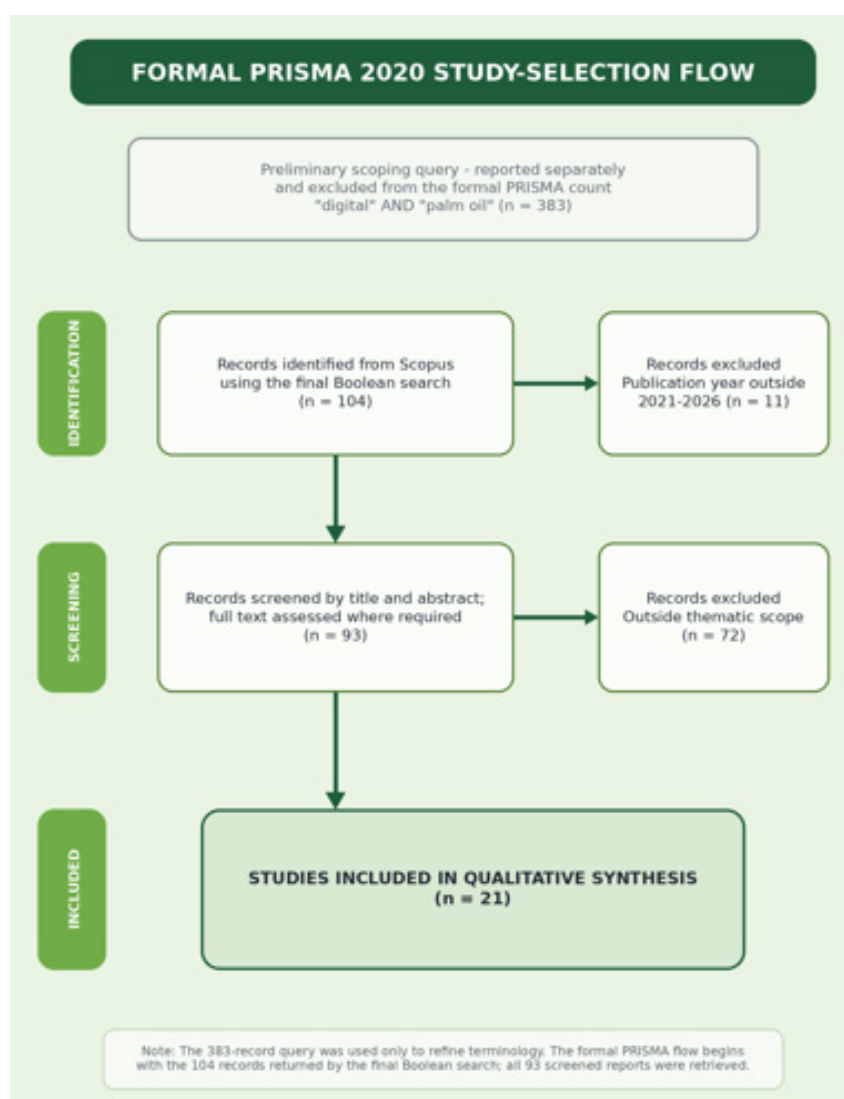


Figure 1 Corrected PRISMA 2020 flow diagram for the formal study-selection process.

A structured extraction matrix was used to record author and year, geographic coverage, publication and study design, AI or digital technique, supply-chain segment, principal finding, and relevance to the review question. Each included publication was assigned to one dominant thematic cluster to prevent double counting in the frequency analysis, while cross-theme implications were recorded narratively.

References and bibliographic records were managed in Mendeley Desktop, and a claim-to-source audit was conducted after synthesis so that every empirical statement in the Discussion could be traced to the relevant included publication. Table 1 presents the extraction matrix in condensed form.

Table 1 Characteristics and principal evidence contribution of the twenty-one included publications

Study	Country / coverage	Design / source	AI or digital technique	Supply-chain segment	Principal finding relevant to this review
Falgenti et al. ³⁹	Indonesia: Rokan Hulu, Riau	Empirical field application	Gap analysis and machine-learning cluster analysis	Plantation and fresh fruit bunch collection	Classified smallholder plantations as trusted, potential, or low-potential, supporting differentiated handling of certified and uncertified fruit at the weighbridge.
Rustiadi et al. ¹⁰	Indonesia: Jambi Province	Applied spatial-system study; conference publication	OPTIMAL-IPB precision spatial information system	Smallholder plantation registration and mapping	Detected plantation position, area, and spatial suitability to address administrative invisibility affecting traceability and certification.

Table 1 Continued..

Study	Country / coverage	Design / source	AI or digital technique	Supply-chain segment	Principal finding relevant to this review
El Hathat et al. ¹³	Indonesia: Sumatra; cradle-to-port chain	Empirical supply-chain case	Deep learning, blockchain, Hyperledger Fabric smart contracts	Cultivation, processing, logistics, and emissions accounting	Created an auditable record for tracking greenhouse-gas emissions across a defined cradle-to-port palm oil supply chain.
VanderWilde et al. ⁴⁰	Guatemala linked to global markets	Observational remote-sensing and spatial analysis	Remote sensing and spatial analysis	Certification and deforestation outcomes	Found no statistically significant reduction in deforestation for certified plantations relative to non-certified plantations.
Jain et al. ⁴¹	Palm-oil supply-chain case; country not specified in the manuscript	Applied modelling case	Machine-learning carbon estimation, hotspot detection, and explainability	Cradle-to-gate environmental accounting	Identified cultivation as the principal emissions hotspot and demonstrated explainable AI for decarbonisation decisions.
Liu et al. ¹⁴	China–Indonesia / ASEAN palm-oil trade	Forecasting and sustainability modelling	Time-series generative adversarial network and green supply-chain index	Import forecasting and sourcing allocation	Integrated demand forecasting with deforestation intensity, land-use efficiency, and certification status to support sustainability-oriented sourcing.
Rincón-Guio et al. ⁴²	Global palm-oil literature	Integrative conceptual review of 46 studies	Blockchain, machine learning, and circular-economy integration	Multi-stage supply-chain governance	Proposed an integrated traceability and certification model while identifying implementation cost and smallholder exclusion as major barriers.
Ann et al. ⁴³	Malaysia	Survey-based predictive modelling; n = 186	Linear regression, decision tree, and Random Forest	Organisational adoption readiness	Identified perceived usefulness and perceived ease of use as significant determinants of blockchain-adoption readiness.
Deviarti and Nevara ⁴⁴	Global palm-oil agroindustry literature	Systematic / conceptual review	IoT, AI, blockchain, and digital green management accounting	Real-time monitoring and sustainability reporting	Outlined an integrated monitoring framework but found the managerial-accounting mechanisms needed for implementation to be underexplored.
Lim et al. ⁴⁵	Palm-oil industry literature	Review using HAZOP	Industry 4.0 features including blockchain, cloud computing, and smart imaging	Sector-wide digital transformation	Identified 13 technology-development gaps and proposed 23 recommendations for industry adaptation.
Zaki et al. ⁴⁶	Global oil-palm literature; 98 studies	Literature review	Industry 4.0 and AI applications	Plantation and processing	Showed that mapping, disease detection, and fruit grading dominate the literature, while transparency remains a secondary contribution.
Yan et al. ⁴⁷	Palm-oil industry; geographic scope not specified in the manuscript	Scholarly book chapter / narrative overview	IoT, AI, and automation	Supply-chain technology adoption	Described anticipated supply-chain benefits and persistent implementation barriers, without reporting an independent operational validation.
Judijanto and Nurhayati ⁴⁸	Global literature; 38 studies	Interdisciplinary review	AI analytics, blockchain, and metaverse platforms	Stakeholder collaboration and knowledge sharing	Associated digital platforms with transparency and collaboration but identified infrastructure and interoperability constraints.
Kanniah and Yu ⁴⁹	Global / geospatial coverage	Scholarly book / technical overview	IoT, AI, blockchain, and remote sensing	Plantation monitoring and environmental change	Presented an integrated geospatial framework; traceability is an indirect implication rather than the primary evaluated outcome.
Khan et al. ⁵⁰	Global literature; 61 papers	Review	Machine-learning methods	Precision agriculture	Found that yield and fruit classification dominate oil-palm machine-learning research, with predictive analytics still unevenly developed.
Judijanto and Nurhayati ⁵¹	Global literature; 35 studies	Systematic review	Convolutional neural networks and ensemble models	Yield, disease detection, and process optimisation	Reported strong predictive performance but identified no equivalent thematic category for supply-chain traceability.

Table 1 Continued..

Study	Country / coverage	Design / source	AI or digital technique	Supply-chain segment	Principal finding relevant to this review
Akhtar et al. ⁵²	Global literature	Review	Remote sensing and AI	Plantation monitoring and illegal-deforestation detection	Described certification-relevant monitoring capability while remaining focused on plantations rather than product-level provenance.
Noviyanto et al. ²⁸	Oil-palm concession case; location not specified in the manuscript	Empirical remote-sensing modelling	Random Forest, Gradient Boosting, XGBoost, and multi-sensor indices	Concession-scale carbon accounting	Achieved R ² values of 0.86–0.88 for carbon-stock prediction, supporting environmental verification rather than chain-of-custody tracking.
Masolele et al. ⁵³	Africa	Empirical deep-learning mapping	Deep-learning land-use classification	Post-deforestation land-use monitoring	Mapped land uses following forest loss and identified oil palm among commodity drivers; contribution is contextual rather than supply-chain specific.
Nggofur et al. ¹²	Indonesia, Malaysia, the Philippines, and Thailand	Empirical spectroscopy and machine learning	1H NMR, PCA, t-SNE, and partial least-squares regression	Product-origin and compositional authentication	Discriminated geographical origin and predicted key fatty-acid compositions of crude palm oil.
Shi et al. ⁵⁴	Global vegetable-oil literature	Review	NMR spectroscopy and chemometrics	Product quality and authentication	Identified advanced machine learning and portable analytical platforms as emerging directions for on-site oil authentication.

Note: “Country / coverage” reports the location or scope stated in the manuscript and included publication; where the manuscript did not identify a country, this is stated rather than inferred. Review and conceptual publications are retained because they met the eligibility criteria, but their evidentiary role is differentiated in Table 2.

Because the corpus combines primary empirical studies, applied modelling, systematic and narrative reviews, conference proceedings, and scholarly book chapters, methodological quality and risk-of-bias concern were evaluated through a design-sensitive five-domain matrix adapted from the principles of the Mixed Methods Appraisal Tool (Hong et al., 2018). The domains assessed were: (A) clarity and fit of the research aim and design; (D) transparency of data or source selection; (T) transparency of analytical procedures; (V) validation, triangulation, or robustness checking; and (C) proportionality between the evidence presented and the claims advanced. Each domain was

coded Y (criterion met), P (partially met or incompletely reported), or N (not met). Overall concern was rated low when the publication met nearly all domains, moderate when limitations reduced certainty without invalidating its contribution, and high when two or more major domains were absent or when the publication was principally conceptual. No publication was excluded solely on the basis of appraisal; instead, the ratings were used to weight the confidence placed on each claim in the Discussion. Table 2 reports the study-level ratings and the main reason for each overall judgement.

Table 2 Design-sensitive methodological-quality and risk-of-bias appraisal of included publications (codes and rating rules are defined in the Method)

Study	Design / source	A	D	T	V	C	Overall concern	Main appraisal rationale
Falgenti et al. ³⁹	Empirical field / ML	Y	P	P	P	Y	Moderate	Operationally relevant, but reporting detail and external validation are limited.
Rustiadi et al. ¹⁰	Applied spatial system	Y	P	P	P	Y	Moderate	Clear applied purpose; conference-format reporting limits methodological detail and validation.
El Hathat et al. ¹³	Empirical supply-chain case	Y	Y	Y	P	Y	Moderate	Transparent architecture, but evidence comes from one supply-chain implementation.
VanderWilde et al. ⁴⁰	Observational spatial analysis	Y	Y	Y	Y	Y	Low	Clear design, transparent spatial analysis, and outcome comparison support the finding.
Jain et al. ⁴¹	Applied ML case	Y	Y	Y	P	Y	Moderate	Clear methods and explainability; transferability beyond the evaluated chain is uncertain.
Liu et al. ¹⁴	Forecasting / modelling	Y	Y	Y	P	Y	Moderate	Transparent modelling; validation remains scenario- and trade-context dependent.
Rincón-Guio et al. ⁴²	Integrative conceptual review	Y	P	P	N	P	High	Useful conceptual integration, but source selection and empirical validation are limited.
Ann et al. ⁴³	Survey predictive modelling	Y	Y	Y	P	Y	Moderate	Clear survey and model comparison; cross-sectional, single-country evidence limits inference.

Table 2 Continued..

Study	Design / source	A	D	T	V	C	Overall concern	Main appraisal rationale
Deviarti and Nevara ⁴⁴	Systematic / conceptual review	Y	P	P	N	P	High	Relevant framework, but appraisal and operational validation are insufficiently reported.
Lim et al. ⁴⁵	Review with HAZOP	Y	P	Y	P	Y	Moderate	Structured analysis, but evidence selection and external validation are only partly documented.
Zaki et al. ⁴⁶	Literature review	Y	Y	Y	P	Y	Moderate	Broad review; conclusions remain dependent on heterogeneous source quality.
Yan et al. ⁴⁷	Scholarly narrative chapter	Y	P	P	N	P	High	Contextual insight without systematic source appraisal or an operational test.
Judijanto and Nurhayati ⁴⁸	Interdisciplinary review	Y	P	P	N	P	High	Maps emerging technologies, but validation and reproducible appraisal are limited.
Kanniah and Yu ⁴⁹	Scholarly technical overview	Y	P	P	N	P	High	Contextual overview; not designed to test a traceability intervention.
Khan et al. ⁵⁰	Review	Y	Y	Y	P	Y	Moderate	Clear review; heterogeneous applications limit traceability-specific inference.
Judijanto and Nurhayati ⁵¹	Systematic review	Y	Y	Y	P	Y	Moderate	Systematic synthesis, but primary-study heterogeneity remains.
Akhtar et al. ⁵²	Review	Y	Y	Y	P	Y	Moderate	Transparent review; product-level traceability is not directly tested.
Noviyanto et al. ²⁸	Empirical remote-sensing ML	Y	Y	Y	Y	Y	Low	Comparative models and validation metrics support bounded concession-scale claims.
Masolele et al. ⁵³	Empirical deep-learning mapping	Y	Y	Y	Y	Y	Low	Validated large-scale mapping; contextual rather than direct traceability evidence.
Nggofur et al. ¹²	Empirical spectroscopy ML	Y	Y	Y	Y	Y	Low	Sampling and model validation support the product-authentication claim.
Shi et al. ⁵⁴	Review	Y	Y	Y	P	Y	Moderate	Comprehensive review; portable and advanced-ML applications remain prospective.

Results

The formal selection process yielded twenty-one eligible publications for qualitative synthesis. Table 1 provides a study-level audit trail linking each publication to its country or geographic coverage, evidence design, AI or digital technique, supply-chain segment, and principal finding. The corpus comprised ten primary empirical or applied-modelling publications and eleven reviews, conceptual models, conference contributions, or scholarly overviews. The structured appraisal in Table 2 and Figure 2 classified four

publications as low concern, twelve as moderate concern, and five as high concern. High-concern publications were retained for conceptual or contextual insight but were not treated as equivalent to primary empirical validation. Across the full corpus, six dominant thematic clusters characterised the present evidence base: (1) AI- and blockchain-enabled traceability systems, (2) AI-driven forecasting and decarbonisation, (3) organisational readiness and digital transformation, (4) the broader Industry 4.0 landscape, (5) precision agriculture and plantation monitoring, and (6) product authentication through spectroscopic-AI methods.

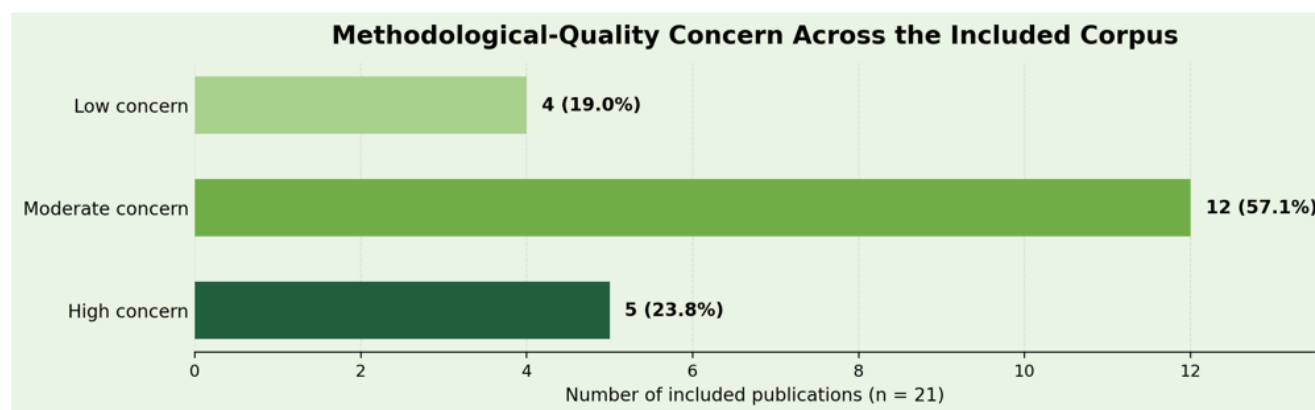


Figure 2 Distribution of methodological-quality concern across the twenty-one included publications.

A thematic frequency analysis indicates that the broader Industry 4.0 and digital-technology landscape and AI applications in precision

agriculture and plantation monitoring were the two most frequently represented themes, each accounting for approximately 24% of

the selected publications (5 of 21). AI- and blockchain-enabled traceability systems were directly addressed in approximately 19% (4 publications), while organisational readiness and digital-transformation frameworks accounted for approximately 14% (3 publications). AI-driven forecasting and decarbonisation and product authentication through spectroscopic-AI methods each represented approximately 9.5% of the corpus (2 publications per theme). Because each publication was assigned to a single dominant theme, these percentages are mutually exclusive and sum to 100%.

The thematic distribution shows that AI research relevant to palm oil remains only partially concentrated on traceability as a direct object of study. Slightly under one-fifth of the included publications addressed product- or transaction-level traceability directly, whereas a much larger share located AI within Industry 4.0 discourse or precision-agriculture tasks such as yield prediction, disease detection, carbon estimation, and plantation mapping. The appraisal results further caution that thematic frequency should not be interpreted as equivalent evidentiary strength: several broad reviews and conceptual contributions identify potential benefits without independently validating an operational chain of custody. The following subsections therefore distinguish direct traceability evidence from adjacent technical capability and contextual support.

AI- and blockchain-enabled traceability systems in the palm oil supply chain

The four publications in this theme provide the most direct evidence for the review's central inquiry, each demonstrating a distinct mechanism by which AI and related digital technologies can be operationalised for product-, plantation-, or emissions-level traceability. A bottom-up fresh fruit bunch traceability system for independent smallholders in Rokan Hulu Regency, Indonesia, combined gap analysis with machine-learning cluster analysis to classify plantations into trusted, potential, and low-potential categories, enabling differentiated handling of certified and uncertified fruit at the weighbridge.³⁹ The OPTIMAL-IPB precision spatial information system was developed to detect the position, area, and spatial suitability of smallholder oil palm plantations in Jambi Province, directly addressing the administrative invisibility that constrains certification and market access.¹⁰ At a broader supply-chain scale, blockchain and deep learning were integrated to track greenhouse-gas emissions across a cradle-to-port palm oil chain in Sumatra, using Hyperledger Fabric smart contracts to create an auditable emissions record.¹³

Notably, the fourth study within this theme offers a critical counterpoint to the assumption that traceability instruments necessarily translate into improved sustainability outcomes: remote sensing and spatial analysis were applied to evaluate deforestation linked to palm oil expansion in Guatemala, reporting that plantations certified under the Roundtable on Sustainable Palm Oil did not exhibit a statistically significant reduction in deforestation relative to non-certified plantations.⁴⁰ Taken together, these four studies indicate that while artificial intelligence and blockchain are technically capable of enabling granular, verifiable traceability at multiple points along the supply chain, the translation of such technical capability into demonstrable sustainability outcomes remains empirically contested rather than assured.

AI-driven forecasting and decarbonisation for supply chain sustainability

Two studies extended the traceability discourse from physical product tracking toward the forecasting and accounting

of environmental impact along the supply chain. A modular decarbonisation accelerator framework combining machine learning-based carbon footprint estimation, hotspot identification, and explainability was proposed and applied to a cradle-to-gate palm oil supply chain, identifying the cultivation stage as the primary emissions hotspot.⁴¹ Extending this logic to an international trade context, Time-series Generative Adversarial Networks were employed to forecast China's palm oil import demand through 2030, integrating these forecasts with a province-level Green Supply Chain Sustainability Index for Indonesia that incorporated deforestation intensity, land-use efficiency, and RSPO certification status to support traceability-based sourcing allocation.¹⁴ Although comparatively few in number, these two studies suggest an emerging methodological trajectory in which generative and explainable artificial intelligence techniques are being adapted to render traceability not merely a matter of physical tracking but of predictive environmental accountability, a direction that appears considerably more nascent than product-level traceability applications.

Organisational readiness and digital transformation frameworks

A further three studies shifted the analytical focus away from the technical performance of artificial intelligence tools and toward the organisational and institutional conditions under which such tools might be adopted. Forty-six peer-reviewed articles were synthesised to develop an integrative conceptual model linking blockchain, machine learning, and circular economy principles to enhanced traceability and certification compliance, while explicitly identifying persistent barriers such as high implementation costs and smallholder exclusion.⁴² The same adoption question was approached empirically through the construction of a predictive readiness model for blockchain adoption in the Malaysian palm oil industry, using machine learning techniques including linear regression, decision tree, and random forest models applied to survey data from 186 respondents, finding that perceived ease of use and perceived usefulness were significant determinants of organisational adoption readiness.⁴³ Readiness was also examined from a managerial accounting perspective, reviewing the intersection of digital green management accounting and circular economy principles in the palm oil agroindustry and proposing a conceptual framework integrating IoT, artificial intelligence, and blockchain to support real-time monitoring and sustainability reporting, while cautioning that the managerial accounting mechanisms required to operationalise such systems remain underexplored.⁴⁴ Collectively, this cluster of studies indicates that the diffusion of AI-enabled traceability technologies in the palm oil sector is constrained less by the technical maturity of the tools themselves than by organisational, financial, and human factors governing their adoption.

The broader industry 4.0 and digital technology landscape in the palm oil sector

The largest thematic cluster within the reviewed literature situated artificial intelligence within the wider context of Industry 4.0 adoption in the palm oil sector, offering valuable comparative insight into how traceability-specific applications are positioned relative to other technological priorities across the industry. Applying a Hazard and Operability Analysis approach, thirteen Industry 4.0 features, including blockchain, cloud computing, and smart imaging, were identified as development gaps for the palm oil industry, with twenty-three recommendations proposed for technological adaptation (Lim et al., 2021). Ninety-eight studies on Industry 4.0 technologies in the oil palm industry were reviewed, reporting that these technologies were most frequently applied to plantation mapping (33.1%), disease

detection (24.8%), and fruit grading (10.8%), with supply chain transparency mentioned as a broader socio-economic contribution rather than a dominant technical focus of the reviewed literature.⁴⁶ The challenges of technological adoption in the palm oil supply chain were similarly discussed, noting that the Internet of Things, artificial intelligence, and automation are anticipated to improve supply chain management, though practical adoption continues to be hindered by implementation barriers.⁴⁷ Metaverse-enabled collaborative platforms were reviewed across thirty-eight studies, finding that artificial intelligence-driven analytics and blockchain contribute to transparency and knowledge sharing among palm oil stakeholders, albeit constrained by infrastructure and interoperability limitations.⁴⁸ These technologies were further situated within a broader geospatial framework, describing the integration of IoT, artificial intelligence, blockchain, and remote sensing for monitoring deforestation and environmental change in oil palm plantations.⁴⁹ The consistency with which this cluster of studies positions traceability and transparency as peripheral benefits of Industry 4.0 adoption, rather than as a primary research objective in their own right, reinforces the broader pattern observed across the reviewed literature: traceability is frequently invoked as a rationale for digital transformation but is rarely the central unit of technical investigation.

AI applications in precision agriculture and plantation monitoring: a comparative benchmark for the traceability research gap

A substantial cluster of the reviewed studies, while not centred on supply chain traceability, provides an important comparative benchmark against which the relative scarcity of traceability-focused research can be assessed. Sixty-one papers published over a decade were reviewed, finding that machine learning applications in oil palm were concentrated in yield and fruit classification tasks and concluding that predictive analytical applications remained comparatively underutilised at the time of the review.⁵⁰ In a more recent systematic review employing the PRISMA protocol, thirty-five studies were analysed, reporting that convolutional neural networks and ensemble models achieved yield prediction accuracies of 80–92% and disease detection F1-scores of 88–92%, with no equivalent thematic category identified for supply chain traceability applications within the dataset. The application of remote sensing and artificial intelligence for plantation management was reviewed, noting that such technologies were recognised by certification bodies including the Roundtable on Sustainable Palm Oil and the International Sustainability and Carbon Certification for detecting illegal deforestation, though the review's principal focus remained plantation-level monitoring rather than product-level traceability. Ensemble machine learning models, including Random Forest, Gradient Boosting, and XGBoost, were applied to predict oil palm carbon stock using multi-sensor satellite indices, achieving R^2 values of 0.86–0.88, with relevance primarily to concession-level carbon accounting rather than traceability.

At a continental scale, a deep learning framework was employed to map land use following deforestation across Africa, identifying oil palm as one of several commodity crops driving forest loss and thereby providing contextual evidence for the broader deforestation-traceability nexus without focusing specifically on the palm oil supply chain.⁵³ When considered alongside the traceability-focused studies discussed earlier, this cluster substantiates, through independent and methodologically varied evidence, the observation that artificial intelligence research in the oil palm sector has developed considerably further in predictive and monitoring applications than in applications explicitly designed for supply chain traceability.

Product authentication and compositional traceability via spectroscopic-AI methods

The final two studies approached traceability from an analytical chemistry perspective, addressing the authentication of palm oil products rather than the digital tracking of physical or transactional supply chains. 1H NMR spectroscopy was integrated with machine learning techniques including principal component analysis, t-distributed stochastic neighbor embedding, and partial least squares regression to authenticate the geographical origin of crude palm oil samples sourced from Indonesia, Malaysia, the Philippines, and Thailand, reporting reliable discrimination of origin above random chance and accurate prediction of key fatty acid compositions.¹² The application of nuclear magnetic resonance spectroscopy combined with chemometrics for the quality assessment and authentication of vegetable oils, including palm oil, was similarly reviewed, noting that the integration of more advanced machine learning models represents an emerging direction for on-site, portable authentication technologies. This theme illustrates a distinct and comparatively underexplored pathway to traceability, one grounded in the physical and chemical verification of product origin and composition rather than in the digital tracking of transactional or logistical data, suggesting that a comprehensive account of AI-enabled traceability in the palm oil sector must draw upon evidence from analytical chemistry as well as from information systems and supply chain management research.

Discussion

This review asked whether the empirical evidence generated by AI applications in the palm oil sector substantiates claims of verifiable, end-to-end supply chain traceability, rather than merely demonstrating capability in adjacent plantation-management tasks. The answer is differentiated. The included corpus provides credible evidence that AI can strengthen several discrete traceability nodes, but it does not yet demonstrate a continuously auditable architecture spanning plantation origin, collection, milling, refining, trade, and end market. This conclusion is based on the twenty-one systematically selected publications in Tables 1 and 2; conceptual background literature is not treated as substitute evidence for the review findings.

At discrete traceability nodes, the evidence is comparatively clear. Machine-learning cluster analysis can support the segregation of smallholder fresh fruit bunches according to documented sustainability status, while precision spatial information can locate and characterise plantations that would otherwise remain outside formal registries. At product level, 1H NMR combined with machine learning can discriminate crude palm oil by geographical origin and predict relevant compositional attributes, creating a physically grounded authentication route that does not depend exclusively on documentary records. At environmental-accounting level, a blockchain and deep-learning case demonstrates auditable greenhouse-gas tracking across a defined cradle-to-port segment. These findings substantiate point-specific capability, but each addresses a bounded verification problem rather than the uninterrupted provenance of a commercially commingled product through all stages.

The certification and deforestation evidence reinforces the need to distinguish traceability instruments from verified sustainability outcomes. Using remote sensing and spatial analysis in Guatemala, VanderWilde et al.⁴⁰ found no statistically significant reduction in deforestation for RSPO-certified plantations relative to non-certified plantations. This study does not evaluate AI-enabled chain of custody directly, but it is the relevant included source for the proposition that certification status alone cannot be assumed to guarantee improved

deforestation performance. The implication is not that certification lacks value, but that claims of traceable and deforestation-free production require independent outcome verification in addition to procedural certification.

A major asymmetry in the evidence base is the much greater maturity of precision-agriculture and plantation-monitoring research compared with end-to-end traceability research. Reviews of oil-palm machine learning and Industry 4.0 report a strong concentration on yield prediction, fruit classification, disease detection, and plantation mapping rather than transaction-level provenance. Remote sensing and AI can support detection of illegal deforestation and concession-scale carbon accounting, and deep learning can map land use following forest loss, but these functions verify biophysical conditions rather than custody transitions between organisations. Accordingly, strong predictive accuracy in plantation management should not be extrapolated automatically into a claim of tamper-resistant supply-chain traceability.

The strongest approximation to multi-stage traceability occurs where AI-generated information is linked to an auditable ledger or to an explicit supply-chain decision framework. El Hathat et al.¹³ connect emissions estimates with Hyperledger Fabric across a cradle-to-port case, while Jain et al.⁴¹ use explainable machine learning to identify carbon hotspots in a cradle-to-gate chain. Liu et al.¹⁴ extend the analytical scope to international sourcing by combining time-series generative modelling with a sustainability index that includes deforestation intensity, land-use efficiency, and certification status. Together these studies show how predictive, accounting, and ledger functions might be combined, but they remain heterogeneous demonstrations rather than replicated validation of a single end-to-end system.

The organisational-readiness evidence helps explain why technical modules have not yet converged into sector-wide practice. Survey-based predictive modelling in Malaysia identifies perceived usefulness and perceived ease of use as significant determinants of blockchain-adoption readiness. The broader conceptual and review literature identifies high implementation costs, limited infrastructure, interoperability problems, human-capability gaps, and the risk of excluding smallholders as persistent barriers. These sources support an implementation explanation for the evidence gap, although the appraisal indicates that several are conceptual or review-based and should therefore inform hypotheses and system design rather than be treated as direct proof of operational effectiveness.

The quality appraisal materially affects interpretation. The four low-concern publications provide the most dependable evidence for remote-sensing outcome assessment, concession-scale modelling, land-use mapping, and spectroscopic authentication. Most direct traceability and decarbonisation demonstrations were rated moderate concern because they are single-site, single-chain, conference-based, or otherwise limited in external validation. The five high-concern publications were retained because they map technologies, barriers, and conceptual linkages, but their claims were weighted as contextual rather than confirmatory evidence. This evidence-weighted reading prevents the synthesis from treating all publication types as methodologically equivalent.

The research question can therefore be answered with a calibrated conclusion: current evidence substantiates AI contributions to plantation identification, origin authentication, carbon estimation, and emissions tracking within defined nodes or segments, but it does not substantiate the broader claim that AI has already delivered verifiable end-to-end traceability across the palm oil supply chain. For industry

and technology developers, the priority is to integrate these validated modules through interoperable identifiers, data-governance rules, and independent verification across organisational boundaries. For certification bodies and regulators, the results support using AI-enabled monitoring and authentication as complements to certification rather than assuming that either technology or certification alone guarantees sustainability outcomes. For researchers, the central task is to evaluate complete chains rather than isolated technical components.

Future research should undertake longitudinal and multi-site evaluations that follow identifiable product or batch records from plantation through collection, mill, refinery, logistics, and market. Studies should report error propagation, data provenance, interoperability, tamper resistance, missing-data treatment, smallholder participation costs, and independent verification, not only model accuracy at a single node. Comparative work across Southeast Asia, West Africa, and Latin America is also needed to test transferability under different land-tenure, infrastructure, and governance conditions. Finally, direct comparisons between AI-enabled and conventional traceability systems would provide a defensible estimate of the incremental value, cost, and distributional consequences of digital adoption.⁵⁵

Limitations

This review has several limitations that delimit the scope of its conclusions. The formal search was restricted to Scopus to maintain a consistent indexing base, but this choice may omit relevant publications indexed only in Web of Science, IEEE Xplore, PubMed, or specialist repositories. The preliminary 383-record query was used for scoping rather than formal identification, and the formal evidence base therefore begins with the 104 records returned by the final Boolean strategy. Future updates should preregister the protocol, document the exact search date, and replicate the final search across multiple databases. The included corpus is methodologically heterogeneous, combining empirical studies, modelling cases, reviews, conference proceedings, conceptual frameworks, and scholarly chapters. Although the design-sensitive appraisal prevents these sources from being treated as equivalent, the adapted common-domain matrix cannot replace every design-specific appraisal instrument. In addition, much of the direct traceability evidence derives from single-case or pilot implementations, and the geographic concentration in Indonesia and Malaysia limits generalisation to West African and Latin American production systems. These constraints mean that the synthesis supports conclusions about demonstrated functions and current evidence gaps, not a definitive estimate of sector-wide effectiveness.

Conclusion

This systematic literature review synthesised evidence from twenty-one eligible scholarly publications to assess whether AI applications in the palm oil sector substantiate claims of verifiable, end-to-end supply chain traceability. The evidence supports reliable contributions at discrete nodes, including classification of smallholder plantations, spatial identification of previously undocumented holdings, geographical and compositional authentication of crude palm oil, concession-scale carbon estimation, and greenhouse-gas tracking within defined supply-chain segments. These applications confirm that AI can strengthen particular verification tasks, especially in upstream contexts where conventional documentation is weakest. The evidence does not yet establish an integrated and continuously auditable chain from plantation to end market. Most AI research relevant to oil palm remains concentrated on precision agriculture, disease detection, yield prediction, plantation mapping, and environmental monitoring, which are technically adjacent to but

analytically distinct from the custody and provenance requirements of end-to-end traceability. Evidence on certification and deforestation further shows that procedural traceability claims cannot be assumed to translate automatically into improved sustainability outcomes.

The structured appraisal reinforces a differentiated interpretation of the literature. Low-concern empirical studies provide credible evidence for specific monitoring and authentication functions, whereas many direct traceability demonstrations remain single-case or pilot-scale and several broader technology claims arise from conceptual or review-based publications. AI-enabled traceability has therefore moved beyond pure aspiration at selected points in the chain, but the integration of those points into a scalable sector-wide architecture remains an emerging achievement constrained by organisational readiness, implementation cost, interoperability, data governance, and institutional incentives. Recognising this distinction is essential for calibrating expectations among industry stakeholders, certification bodies, regulators, and technology providers. The most defensible next step is not to treat AI as a substitute for governance, but to embed validated AI functions within transparent, interoperable, independently audited systems and to test those systems longitudinally across complete supply chains and diverse producing regions.

Acknowledgements

None.

Conflicts of interest

The author declares there is no conflict of interest.

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