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From Financial Stewardship to AI-Enabled Strategic Intelligence: Reimagining Finance for A Sustainable Indonesian Palm Oil Supply Chain

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ABSTRACT: Artificial intelligence is changing the finance function from a predominantly transactional, reporting, and control-oriented activity into a strategic intelligence capability that can combine financial, operational, geospatial, environmental, and supply-chain information. This transformation is particularly relevant to Indonesia's palm oil sector, where large corporate plantations, independent smallholders, cooperatives, mills, refiners, traders, financial institutions, and international buyers operate within a complex network characterised by commodity-price volatility, heterogeneous technological capabilities, sustainability requirements, traceability challenges, and unequal access to finance. This qualitative literature review examines the strategic role of finance in the artificial-intelligence era and synthesises the potential benefits, implications, implementation challenges, and governance requirements of AI-enabled finance within the Indonesian palm oil supply chain. The synthesis identifies major opportunities in financial planning and analysis, cash-flow forecasting, risk management, fraud detection, working-capital optimisation, smallholder credit assessment, capital budgeting, supply-chain finance, traceability, and sustainability-linked decision-making. However, technological value is conditional on data quality, organisational capabilities, human judgement, explainability, accountability, cybersecurity, institutional coordination, and safeguards against algorithmic exclusion. The article proposes an integrated framework in which finance acts as an organisational orchestration layer connecting AI-generated intelligence with capital allocation, risk governance, and sustainable supply-chain outcomes. A staged implementation pathway is recommended, beginning with data foundations and quick wins before advancing toward predictive finance, cross-functional decision intelligence, and ecosystem-level sustainability orchestration.

KEYWORDS: artificial intelligence; finance function; strategic finance; sustainable finance; palm oil; oil palm smallholders; supply-chain finance; AI governance; sustainability; Indonesia.

JEL Classification: G30; G31; O33; Q14; Q56

1. INTRODUCTION

Artificial intelligence (AI) is increasingly challenging long-standing assumptions about what constitutes the finance function inside contemporary organisations. For decades, finance was primarily associated with recording transactions, preparing financial statements, maintaining internal control, safeguarding assets, administering budgets, calculating performance indicators, and ensuring compliance. Digital technologies progressively automated parts of these activities, but recent advances in machine learning, natural-language processing, generative AI, predictive analytics, and intelligent automation are more transformative because they extend beyond transaction processing into prediction, interpretation, decision support, and organisational learning. Recent research also indicates that finance occupations are highly exposed to the productivity effects of generative AI, reinforcing the need for finance leaders to treat AI as a strategic capability rather than a narrow automation tool (Eisfeldt and Schubert, 2025). Consequently, the strategic question facing chief financial officers and other finance leaders is no longer merely how to automate accounting activities, but how to transform financial and increasingly diverse non-financial data into better organisational decisions (Möller, Schäffer and Verbeeten, 2020; Glader and Strömsten, 2020; Enholm et al., 2022; Bahoo et al., 2024).

This transformation should not be interpreted as the automatic substitution of finance professionals by algorithms. The emerging organisational challenge is more accurately described as a reconfiguration of the division of labour between machines and humans. Algorithms may be superior in processing large volumes of structured and unstructured information, detecting patterns, performing repeated classifications, and generating probabilistic forecasts. Human professionals nevertheless remain essential for framing problems, determining materiality, understanding institutional context, evaluating ethical trade-offs, interpreting anomalies, challenging assumptions, and accepting accountability for consequential decisions. Research on human–AI collabouration therefore suggests that successful adoption depends on the architecture of decision rights and the ability to combine algorithmic prediction with human judgement rather than treating automation as an end in itself (Puranam, 2021; Fügener et al., 2022; Jain, Garg and Khera, 2023; Westphal et al., 2023; Raisch and Fomina, 2024).

The transformation is especially significant in industries characterised by biological production cycles, commodity-price uncertainty, spatially dispersed operations, environmental externalities, fragmented suppliers, and complex sustainability requirements. Indonesia's palm oil sector embodies these characteristics. Its supply chain extends from independent and scheme smallholders through plantations, collection points, cooperatives, mills, refineries, oleochemical and food-processing facilities, logistics providers, traders, exporters, financiers, certification bodies, and final buyers. Financial decisions throughout this chain are affected not only by prices, interest rates, exchange rates and production volumes, but also by rainfall, tree age, fertilizer application, plantation productivity, road accessibility, milling capacity, supplier identity, land status, environmental risks, certification, traceability, and regulatory requirements.

The sustainability dimension further complicates financial decision-making. Empirical research on Indonesian palm oil shows that sustainability certification and responsible sourcing are embedded in institutional, economic, social and governance constraints. Independent smallholders frequently face barriers associated with land documentation, certification costs, organisational capacity, knowledge, productivity, finance and access to external facilitation. Certification may generate benefits but these benefits and costs are unevenly distributed, while private and public governance systems themselves remain characterised by overlapping mandates and institutional tensions (Apriani et al., 2020; Santika et al., 2021; Watts et al., 2021; Brandi, 2021; Choiruzzad, Tyson and Varkkey, 2021; Pramudya et al., 2022; Tey et al., 2022; de Vos et al., 2023).

At the same time, the technological foundations required for a more information-rich approach to palm oil management are becoming increasingly feasible. Machine-learning applications have been investigated for plantation detection, crop and yield prediction, tree identification, remote-sensing analysis, and smallholder mapping. Reviews demonstrate that AI and advanced remote sensing can support plantation monitoring and productivity analysis, while high-resolution imagery and deep-learning approaches can improve spatial knowledge concerning fragmented smallholder plantations (Xu et al., 2021; Rashid et al., 2021; Khan et al., 2021; Hilal et al., 2021; Akhtar et al., 2023; Pribadi et al., 2023).

Yet the finance literature and oil palm technology literature largely evolve in parallel. Research on AI in finance focuses on credit scoring, risk management, fraud detection, auditing, forecasting and financial decision-making, while palm oil research generally examines agricultural production, remote sensing, certification, traceability, sustainability governance or smallholder development. The insufficient integration of these literatures leaves an important conceptual gap. An agronomic prediction becomes strategically valuable only when its implications are converted into cash-flow projections, financing requirements, asset valuations, risk measures, investment priorities or supplier interventions. Similarly, remote-sensing evidence concerning plantation conditions becomes economically actionable when connected to credit decisions, insurance, sustainability expenditure, procurement, capital budgeting or supply-chain finance.

Accordingly, this article asks four interconnected questions: how is AI reshaping the strategic role of finance; what economic, operational, financial and sustainability benefits can AI-enabled finance generate within Indonesian palm oil; what technological, organisational, ethical and institutional problems could constrain implementation; and how can responsible AI-enabled finance contribute to a more sustainable and inclusive palm oil supply chain? The paper develops an integrative qualitative literature review rather than a systematic literature review. Its purpose is theoretical and thematic integration across finance, AI, supply-chain management, digital agriculture and palm oil sustainability rather than exhaustive bibliometric enumeration.

The article contributes in three ways. First, it reframes AI in finance from narrow automation toward strategic intelligence and capital orchestration. Second, it contextualises the finance–AI relationship within Indonesia's palm oil ecosystem, including smallholders rather than focusing exclusively on large firms. Third, it proposes an implementation framework that simultaneously considers business value, return on investment (ROI), responsible AI, human oversight and sustainability. This approach is consistent with the proposition that AI becomes economically valuable not simply through technological availability but through complementary organisational capabilities and its integration into decision processes (Mikalef and Gupta, 2021; Enholm et al., 2022; Babina et al., 2024; Li, Zhong and Tong, 2024).

2. LITERATURE REVIEW

2.1 From Financial Stewardship to Strategic Intelligence

Finance traditionally performs several complementary functions. As **steward**, it protects assets, maintains financial integrity and ensures compliance. As **operator**, it runs accounting, treasury, payment and reporting processes. As **strategist**, it evaluates investments, capital structures, acquisitions and long-term scenarios. As **business partner**, it translates operational activity into financial consequences. AI potentially strengthens every role, but its most consequential effect lies in shifting the balance toward anticipatory rather than retrospective finance.

Robotic process automation can reduce manual data-entry and reconciliation work, while AI can extend automation into document interpretation, anomaly identification and exception handling. Auditing research similarly finds that AI can increase analytical scale and efficiency, although successful implementation requires controls and human oversight (Harrast, 2020; Almufadda and Almezeini, 2022; Fedyk et al., 2022; Rikhardsson et al., 2022). Deep-learning techniques also demonstrate the possibility of combining financial and textual information in fraud detection, illustrating how finance can analyse information that historically remained outside conventional accounting systems (Craja, Kim and Lessmann, 2020).

Machine learning is also relevant to financial planning and analysis (FP&A), where forecast accuracy, scenario evaluation and the processing of high-dimensional data may improve managerial planning. However, methodological sophistication does not eliminate the need to understand causal relationships, model limitations and uncertainty (Wasserbacher and Spindler, 2022). Generative AI adds opportunities for management reporting, narrative analysis, summarisation, interrogation of financial databases and decision-support interfaces, but emerging research also highlights risks involving hallucination, data security, professional judgement and accountability (Dong, Stratopoulos and Wang, 2024; Zhao and Wang, 2024). More recent accounting scholarship argues that AI is now reshaping both professional workflows and the production and interpretation of accounting knowledge, which increases the importance of AI fluency alongside conventional domain expertise (Stratopoulos and Wang, 2025).

The strategic significance of AI becomes clearer from the resource-based and dynamic-capability perspectives. AI capability comprises much more than algorithms; it requires data, infrastructure, technical skills, managerial capabilities and interdepartmental coordination. Mikalef and Gupta (2021) demonstrate that organisational AI capability is positively associated with creativity and performance, while broader reviews conclude that the conversion of AI investment into business value depends on complementary organisational resources (Enholm et al., 2022). Evidence that AI-intensive firms can experience higher growth and innovation reinforces the argument that AI should be treated as an organisational capability rather than a stand-alone software investment (Babina et al., 2024).

For finance, this perspective has an important implication: the CFO's AI agenda should not begin by asking which algorithm to purchase. It should begin by identifying strategically important decisions, the uncertainties surrounding those decisions, the information needed to reduce those uncertainties, and the governance needed to make AI-supported decisions accountable. This reverses technology-first implementation into a **decision-first architecture**.

2.2 AI, Financial Risk and Responsible Decision-Making

Financial applications of AI are particularly attractive where large data volumes and repeated predictions coexist. Machine learning has been used to improve credit classification and credit-rating prediction, while explainable AI has become increasingly relevant because a highly accurate prediction may still be unacceptable if the decision-maker cannot understand or justify it (Li et al., 2020; Bussmann et al., 2020; Bussmann et al., 2021). Agricultural finance provides analogous evidence: machine-learning models can improve predictions of agricultural loan delinquency, although the economic consequences of false positives and false negatives remain important for model selection (Chen, Katchova and Zhou, 2021).

This is highly relevant to palm oil smallholders. An AI-based credit model could combine historical FFB deliveries, yields, farm age, transaction records, agronomic indicators, cooperative membership, geospatial characteristics and repayment histories. Such a model could reduce information asymmetry and potentially enable lenders to distinguish between borrowers more accurately than conventional collateral-based methods. However, if the available data systematically favour farmers already connected to formal mills, cooperatives or certification programmes, AI may reproduce and intensify historical inequalities. A farmer with insufficient digital history may be interpreted algorithmically as high risk when the underlying problem is missing data rather than weak economic potential.

Explainability is therefore not an optional technical convenience. Different stakeholders require different forms of explanation: a data scientist may need feature importance and model diagnostics, a credit committee may need understandable risk drivers, a borrower needs a comprehensible explanation for a credit outcome, and auditors or regulators require evidence of model governance and accountability. Research consequently emphasises audience-dependent explainability and broader principles of accuracy, fairness and sustainability in financial AI (Hadji Misheva et al., 2021; Fritz-Morgenthal, Hein and Papenbrock, 2022; Giudici and Raffinetti, 2023). Recent work on responsible AI for credit scoring similarly shows that fairness, explainability, operational controls and governance need to be treated jointly rather than as isolated model characteristics (Mathen, 2025).

Accounting and audit research raises similar concerns about objectivity, privacy, transparency, accountability and trustworthiness. AI does not eliminate ethical judgement because decisions about data selection, objective functions, thresholds and intervention criteria embody normative choices (Munoko, Brown-Liburd and Vasarhelyi, 2020; Lehner et al., 2022).

2.3 Organizational AI Governance

AI governance can be understood as the organisational system through which decision rights, responsibilities, standards and monitoring procedures are established for AI applications. Mäntymäki et al. (2022) position AI governance as part of broader corporate and IT governance, while Birkstedt et al. (2023) show that the literature increasingly focuses on translating high-level principles into organisational practices. Ethics-based auditing offers one mechanism for evaluating whether AI development and deployment are consistent with organisational principles, although practical implementation encounters familiar governance challenges such as standardisation, scope definition, communication and organisational change (Mökander and Floridi, 2023).

Global reviews of AI ethics guidelines reveal widespread convergence around transparency, fairness, accountability, privacy, security and human oversight, but they also reveal the danger of relying on principles without implementation mechanisms (Kluge Corrêa et al., 2023; Attard-Frost, De los Ríos and Walters, 2023). More recent organisational research reinforces the need for responsible-AI practices covering structures, relationships and procedures throughout the AI lifecycle rather than treating governance as a one-time model-validation exercise (Papagiannidis, Mikalef and Conboy, 2025). Algorithm review boards and other cross-functional oversight mechanisms can complement existing governance, particularly for applications with significant financial or human consequences (Hadley, Blatecky and Comfort, 2025). For palm oil, responsible AI governance should therefore connect finance governance, data governance, model governance, sustainability governance and supply-chain governance. An isolated AI committee cannot solve problems caused by inaccurate smallholder identities, inconsistent plantation boundaries, missing legal documents or incompatible information systems. Governance must begin with the reliability and provenance of data.

2.4 Sustainable Palm Oil as a Financial and Information Problem

Indonesia's sustainable palm oil challenge is frequently framed as an agronomic, environmental or certification problem, but it is simultaneously a financial and information-management problem. Sustainability measures generate costs, investment requirements, potential productivity benefits, access to differentiated markets, financing implications and risks. Independent smallholders may lack resources to finance certification or replanting, while companies must allocate capital among productivity, traceability, environmental management, mill efficiency, infrastructure and community programmes. Recent Indonesian evidence identifies persistent disconnects between sustainability ambitions and financing arrangements, including limited incentives, smallholder access barriers and administrative constraints surrounding replanting finance (Wahid et al., 2024).

Studies of certification demonstrate that smallholder participation cannot be understood independently of financial incentives and institutional capacity. Apriani et al. (2020) identify dependence on external support among smallholders pursuing non-state certification. Watts et al. (2021) show that structural disadvantages constrain independent smallholder certification, while Pramudya et al. (2022) emphasise the importance of incentives in mandatory certification. Tey et al. (2022) explicitly analyse financial costs and benefits of RSPO certification, illustrating why finance is central to sustainability adoption rather than merely an administrative support function.

Oil-palm cultivation can improve household welfare, yet farmers remain exposed to economic risk, which creates a rationale for better credit, savings, insurance and risk-management mechanisms (Mehraban et al., 2021). Certification outcomes likewise do not translate automatically into uniform improvements in welfare; effects vary with context and implementation (Santika et al., 2021).

At the governance level, the interaction between RSPO, ISPO, corporate commitments and national policy demonstrates that sustainable palm oil is embedded in a complex regime rather than a single standard. Private and public sustainability governance can be complementary but may also generate competing incentives and implementation difficulties (Brandi, 2021; Choiruzzad, Tyson and Varkkey, 2021; Putri et al., 2022). Corporate zero-deforestation goals further generate tensions between environmental targets, economic competitiveness and smallholder inclusion (Grabs and Garrett, 2023).

Thus, finance must increasingly assess not only "How much does sustainability cost?" but also "What risks are avoided?", "What future market access is protected?", "Which suppliers require financing or technical assistance?", and "What is the economic cost of exclusion, non-compliance, inaccurate traceability or delayed replanting?" AI can contribute to these questions only if financial and sustainability data become interoperable. This requires common definitions, reliable identifiers and governance arrangements that allow operational and sustainability evidence to be translated into decision-grade financial information.

3. METHOD

This study employs a qualitative literature review (QLR) rather than a systematic literature review. Its objective is interpretive synthesis across several bodies of scholarship that have not traditionally been analysed together: AI and organisational capability; AI in accounting and finance; responsible AI; human–AI decision-making; sustainable supply-chain management; agricultural finance; oil palm digitalisation; smallholder development; certification; traceability; and Indonesian palm oil governance.

The review is therefore not designed to produce an exhaustive universe of publications or a PRISMA-based count of identified, screened and excluded documents. Such a design would be inconsistent with the principal research problem, which requires conceptual integration across disciplines with different terminology, units of analysis and research traditions. Instead, literature was identified iteratively and purposively, giving priority to peer-reviewed journal research published from 2020 onward, with particular attention to reputable international journals and empirical or theoretically significant studies. Citation chaining and thematic expansion were used when one literature stream exposed a concept relevant to another.

The practitioner-oriented material supplied as the initial input for this study was treated as a set of **sensitising themes** rather than academic evidence. In particular, six themes—strategic finance, identification of AI opportunities, business-case development and ROI, AI governance, AI-supported decision-making, and quick wins—were used to help frame the cross-disciplinary literature synthesis. Scholarly claims in the article, however, are grounded in peer-reviewed literature.

The synthesis proceeded in four interpretive stages. First, studies were coded according to the primary role assigned to AI: automation, prediction, classification, detection, optimisation, decision support or generative assistance. Second, financial implications were coded into accounting operations, FP&A, treasury, investment, risk, audit, credit, supply-chain finance and sustainability finance. Third, Indonesian palm oil studies were interpreted through themes of smallholder inclusion, certification, governance, traceability, productivity, environmental risk and supply-chain complexity. Fourth, these categories were integrated through an AI-capability and socio-technical lens to identify relationships between data, algorithms, human judgement, organisational routines and sustainability outcomes.

The method deliberately distinguishes three evidentiary levels. The first comprises applications directly supported by finance research, such as forecasting, credit scoring and anomaly detection. The second comprises technological capabilities documented in oil palm research, including remote sensing, plantation detection and yield prediction. The third comprises integrative propositions generated by this review—for example, connecting satellite-derived plantation information with credit appraisal or incorporating traceability signals into working-capital and procurement decisions. These propositions should not be interpreted as claims that every application is already deployed commercially within Indonesian palm oil corporations.

This distinction is essential because the literature demonstrates both the promise and the limitations of AI. Reviews of AI business value indicate that organisations often struggle to translate technology into performance because benefits depend on data, integration and complementary capabilities (Mikalef and Gupta, 2021; Enholm et al., 2022). Supply-chain reviews similarly show substantial potential for AI but underline data, integration and organisational barriers (Toorajipour et al., 2021; Naz et al., 2022).

Several methodological limitations should be acknowledged. Because this study is a qualitative rather than systematic literature review, the literature base is purposive and interpretive and does not support claims of exhaustive coverage or quantitative effect estimation. The evidence base is also asymmetric: AI-enabled finance is comparatively well documented in banking, accounting and general corporate settings, whereas direct empirical evidence on AI-enabled finance in Indonesian palm oil remains limited. Accordingly, cross-domain applications proposed in this article are presented as theoretically grounded and practically plausible propositions that require further sector-specific empirical validation.

4. RESULTS: THEMATIC FINDINGS

4.1 Theme 1: Finance Is Moving from Historical Stewardship toward Forward-Looking Intelligence

The literature supports a shift in finance from retrospective reporting toward predictive and prescriptive decision support. Traditional financial reporting primarily explains what has happened; AI-enhanced finance can increasingly estimate what may happen, why it may happen, and which intervention could improve the outcome. The transformation does not eliminate stewardship. Instead, stewardship becomes the trustworthy data and control foundation upon which strategic intelligence depends.

In palm oil, the distinction is especially meaningful. Conventional budgeting may use historical yields, average fertilizer expenditure and previous commodity prices. AI-enabled FP&A could instead combine tree-age profiles, rainfall forecasts, historical FFB yields, field operations, fertilizer regimes, mill utilisation, CPO extraction rates, logistics costs and commodity-price scenarios. Oil-palm research already demonstrates the technical viability of machine-learning approaches to yield forecasting and plantation analysis (Rashid et al., 2021; Khan et al., 2021; Hilal et al., 2021). The finance opportunity is to translate those predictions into revenues, costs, working-capital requirements, debt-service capacity and investment decisions.

The conceptual shift is illustrated in Figure 1, which links data foundations, AI-enabled analytics, finance processes, strategic decisions and sustainable outcomes. The sequence also highlights that governance and feedback must operate across the entire decision cycle rather than being added after a model is deployed.

Figure 1 positions finance between increasingly diverse operational data and ultimate corporate and sustainability outcomes. The figure deliberately places governance around the entire cycle because data that are inaccurate, biased or insufficiently governed can contaminate prediction and, ultimately, capital-allocation decisions.

Figure 1. The AI–Finance–Sustainable Palm Oil Intelligence Loop

Source: Author synthesis based on Mikalef and Gupta (2021), Enholm et al. (2022), Mäntymäki et al. (2022), Naz et al. (2022) and Papagiannidis, Mikalef and Conboy (2025).

Figure 1 emphasises that AI does not create sustainability directly. AI generates analyses whose value depends on the decisions they inform. Finance becomes critical because it converts heterogeneous evidence into comparable economic consequences and determines whether organisational resources are actually committed. A deforestation-risk indicator that remains on an ESG dashboard may have little operational effect; when incorporated into supplier financing, procurement conditions, capital expenditure or risk pricing, it becomes part of corporate decision architecture.

4.2 Theme 2: Predictive FP&A Can Connect Biological Production to Financial Planning

Oil palm is a perennial crop with production patterns influenced by biological age, weather, field management, disease, harvest cycles and input use. This means that financial forecasting depends on agronomic uncertainty. Separating operational forecasts from finance creates predictable weaknesses: finance receives static production assumptions, while plantation teams may not see how small changes in yield translate into liquidity, covenant, investment or profitability consequences.

Machine-learning research demonstrates opportunities for forecasting oil palm yields and identifying plantations through remote sensing (Xu et al., 2021; Rashid et al., 2021; Khan et al., 2021). Remote-sensing and AI reviews also highlight the increasing ability to integrate satellite, UAV and plantation information for monitoring and management (Akhtar et al., 2023).

AI-enabled FP&A can therefore create a rolling link between the biological system and the financial system. If a model anticipates lower FFB production in a region because of rainfall patterns or tree-age composition, finance can evaluate the impact on mill throughput, processing cost per tonne, procurement requirements, cash inflows and debt servicing. Conversely, predicted crop increases can inform working capital, transport capacity and sales planning. Machine learning in financial forecasting offers precisely this advantage of processing complex relationships, provided that the organisation recognises model uncertainty and does not confuse prediction with certainty (Wasserbacher and Spindler, 2022).

Scenario intelligence is equally important. CPO prices, fertilizer prices, fuel costs, exchange rates and interest rates can interact with operational variables. AI-based analytics could run multiple combinations and identify thresholds at which a previously attractive capital project becomes vulnerable. In this role, finance is not simply producing a budget; it is creating a continually updated economic representation of the enterprise.

4.3 Theme 3: Treasury and Working-Capital Management Offer High-Value Applications

Palm-oil companies manage substantial working-capital flows across procurement, payroll, fertilizer, transportation, inventories, sales, taxes and debt. Treasury decisions become more difficult when harvest patterns and commodity prices fluctuate. AI-assisted cash forecasting can improve visibility over future liquidity by incorporating seasonality and operational drivers that may be missed by simple trend models.

Potential applications include daily and weekly cash forecasting, identification of abnormal payment patterns, optimisation of payment timing within supplier terms, receivables prioritisation and liquidity stress testing. Robotic automation can first standardise repetitive processes, while machine learning adds probabilistic forecasting and exception detection (Harrast, 2020; Wasserbacher and Spindler, 2022).

The strategic benefit is not restricted to lower finance department costs. More accurate working-capital information can reduce precautionary cash balances, prevent liquidity shortages, improve borrowing decisions and allow capital to be redeployed. For palm oil groups with multiple estates, mills and subsidiaries, the value may also arise from identifying cash inefficiencies that remain invisible within fragmented entity-level systems.

A prudent implementation sequence is therefore to distinguish **automation value** from **intelligence value**. Automatically reconciling accounts saves hours. Predicting liquidity shortfalls creates decision value. Detecting abnormal procurement payments protects value. Combining all three creates a stronger financial-control ecosystem.

4.4 Theme 4: AI Can Strengthen Risk Management—but Only with Explainability

The risk landscape in palm oil is multidimensional. It includes commodity-price risk, foreign-exchange risk, operational disruptions, weather, crop failure, fire, logistics interruptions, counterparty default, fraud, regulatory risk, certification risk, deforestation exposure, reputational risk and market-access risk. Conventional risk registers often struggle to capture interdependencies among such risks.

AI can strengthen risk management through pattern recognition and predictive classification. Finance research demonstrates applications in credit ratings, fraud detection and explainable risk models (Li et al., 2020; Craja, Kim and Lessmann, 2020; Bussmann et al., 2020, 2021). Yet the same literature warns that accuracy alone cannot justify decisions when outcomes affect borrowers, suppliers, employees or investors.

For example, a supplier-risk model could flag an FFB supplier because of unusual spatial patterns, irregular deliveries or incomplete documentation. The finance and procurement teams must know whether the signal reflects fraud, seasonal variation, legitimate changes in sourcing or insufficient data. Automatic suspension without human review could create social and commercial harm. Responsible implementation therefore requires risk tiering: low-impact applications may be highly automated, while consequential decisions should trigger human review.

This is where human-in-the-loop finance becomes essential. Human oversight should not mean a ceremonial approval after an algorithm has effectively decided. Decision makers must have sufficient information and authority to challenge the model. Research on human–AI collabouration shows that performance depends on the way decision rights are allocated and the capacity of users to evaluate AI recommendations (Puranam, 2021; Fügener et al., 2022; Westphal et al., 2023).

4.5 Theme 5: AI Could Transform Smallholder Finance

One of the most consequential opportunities lies outside the corporate finance department itself. Independent smallholders frequently face constraints in accessing affordable finance, especially for replanting, certification, farm improvements and productivity-enhancing inputs. Conventional agricultural credit is constrained by information asymmetry, documentation, collateral requirements and the difficulty of assessing farm-level economic risk.

Oil palm research shows that smallholder welfare can benefit from cultivation while exposure to economic risk remains substantial (Mehraban et al., 2021). Certification research also documents financial and institutional barriers affecting smallholder participation (Apriani et al., 2020; Watts et al., 2021; Tey et al., 2022; de Vos et al., 2023). Recent discrete-choice evidence from Indonesia further indicates that practical farm-management training and cash premiums can materially increase smallholders' willingness to adopt certification, highlighting the importance of incentive design (Reich and Mußhoff, 2025). These findings suggest that sustainability cannot be achieved solely by imposing requirements; financing, incentives and technical support must help farmers undertake the transition.

AI-supported agricultural credit could use alternative information where legally and ethically appropriate: historical deliveries to mills, consistency of production, farm age, cooperative membership, geospatial characteristics, previous input purchases, payment records and agronomic performance. Machine-learning evidence from agricultural loan prediction suggests that non-linear approaches can improve identification of financial stress, although model selection must reflect the different costs of classification errors (Chen, Katchova and Zhou, 2021).

However, the social implications require careful attention. A smallholder who has fewer recorded transactions may appear riskier because the farmer is less digitised. This would transform the digital divide into a financing divide. An inclusive model therefore requires explicit procedures for missing data, alternative verification channels, appeal mechanisms and human review. AI should broaden the information available for financing, not redefine lack of digital history as lack of creditworthiness.

Cooperatives can play an important intermediary role. A cooperative could aggregate farmer information, facilitate documentation, support financial literacy, verify production and negotiate finance. AI can then assist with portfolio-level assessment rather than requiring every smallholder to interact independently with sophisticated digital systems.

4.6 Theme 6: Traceability Data Can Become Financial Data

Traceability is often treated as an ESG or compliance function, but it increasingly has direct financial implications. If a buyer, lender or investor differentiates suppliers by sustainability risk, the quality of traceability information affects revenue, financing conditions, reputational exposure and potentially asset value.

Scientific research demonstrates the feasibility of advanced analytical techniques for palm oil geographical traceability and authenticity verification (Ramli et al., 2020). Remote sensing can identify plantation characteristics, while deep-learning approaches can support smallholder mapping that is otherwise difficult because farms are small, irregular and geographically dispersed (Pribadi et al., 2023).

The finance implication is important: traceability should be understood as **decision-grade information infrastructure**. Supplier data can contribute to procurement decisions, counterparty-risk assessment, financing terms, inventory valuation assumptions and sustainability-linked capital allocation. The distinction between financial and non-financial information becomes increasingly artificial when environmental or traceability risks can materially affect future cash flows.

Supply-chain technology research reinforces this integration. AI can improve supply-chain forecasting, risk detection and optimisation, while sustainable supply-chain applications highlight the importance of using technology to connect economic and sustainability objectives (Toorajipour et al., 2021; Naz et al., 2022). Blockchain research on palm oil emissions and traceability further illustrates the potential value of immutable information structures, although technology cannot compensate for unreliable data entry or weak governance (El Hathat et al., 2023).

The relationship is summarised in Figure 2, which maps AI-enabled finance use cases across the palm oil value chain. The figure also shows that traceability, data governance, AI governance, auditability and cybersecurity are cross-cutting capabilities rather than isolated technical functions.

Figure 2 shows how financial AI applications differ along the palm oil value chain but can ultimately be connected into one integrated information environment. The central insight is that finance can act as the common language through which operational and sustainability signals are translated into decisions.

Figure 2. AI-Enabled Finance across the Indonesian Palm Oil Supply Chain

Source: Author synthesis based on Toorajipour et al. (2021), Naz et al. (2022), Ramli et al. (2020), Pribadi et al. (2023), Watts et al. (2021) and Al-Sartawi, Hussainey and Razzaque (2022).

Figure 2 also reveals why adoption cannot be company-centric alone. A highly digitised plantation company may still depend on poorly digitised upstream suppliers. The economic value of AI therefore depends partly on ecosystem interoperability.

4.7 Theme 7: AI Can Improve Capital Allocation and Replanting Decisions

Capital budgeting is one of finance's most strategic responsibilities. Palm-oil companies must make long-term investments in replanting, mills, roads, storage, transport, digital infrastructure, methane capture, renewable energy, wastewater treatment, mechanisation and downstream processing. These investments involve uncertain cash flows over long horizons.

AI can enrich—not replace—conventional discounted cash-flow analysis. Traditional NPV models commonly rely on a limited number of deterministic assumptions. AI-supported investment analysis could generate probability distributions informed by operational and market data and run more sophisticated scenarios. Evidence that AI adoption can improve aspects of corporate financial asset allocation, particularly where firms possess strong absorptive and adaptive capabilities, supports this broader direction (Li, Zhong and Tong, 2024).

Replanting illustrates the potential. Delaying replanting may preserve short-term cash flow but produce declining yields and rising maintenance costs. Immediate replanting requires financing and temporarily reduces production. A more sophisticated decision model can incorporate tree age, expected yield curves, input costs, labour, commodity-price scenarios, financing costs, smallholder household cash requirements and alternative replanting schedules. Finance can then compare not merely static NPVs but resilience under multiple scenarios.

At the sectoral level, land expansion is not the only route to higher output. Research on sustainable land availability underscores the importance of yield improvement, environmental protection and strategic planning rather than indiscriminate expansion (Tapia, Doliente and Samsatli, 2021). AI-enabled finance can support this transition by directing capital toward productivity improvements on existing land where economically, socially and environmentally appropriate.

4.8 Theme 8: Building the Business Case Requires a Broader Concept of ROI

An important obstacle to AI adoption is the gap between technological enthusiasm and financial justification. Pilot projects are often launched because AI is perceived as strategically necessary rather than because the organisation has articulated a measurable economic mechanism. This creates the possibility of numerous experiments with weak ownership and little scalable value.

Finance should therefore develop a structured **AI business case**. The numerator of ROI should include direct cost savings, reduced losses, working-capital improvements, additional revenue, improved forecasting, avoided fraud and better asset utilisation. It should also include reasonably measurable risk-avoidance benefits, such as reduced probability of supply-chain disruption or non-compliant procurement. The denominator should include more than software licences: data cleansing, integration, cloud infrastructure, model development, cyber controls, training, governance, monitoring, change management and ongoing maintenance must be recognised as part of total cost.

Some benefits will not be immediately monetisable. Improved traceability may preserve market access; better smallholder data may increase future financing capacity; stronger governance may reduce the probability of rare but severe losses. These should not be forced into artificial precision. Instead, finance can classify benefits according to confidence and use sensitivity analysis.

This broader perspective is consistent with the literature showing that AI business value depends on organisational resources and may emerge with delay because firms must invest in complementary capabilities (Mikalef and Gupta, 2021; Enholm et al., 2022). Firm-level evidence on AI and innovation similarly suggests that economic value can arise through expanded opportunity sets rather than solely through cost reduction (Babina et al., 2024). Sustainable-finance research likewise argues that AI can support the integration of sustainability considerations into financial decisions (Al-Sartawi, Hussainey and Razzaque, 2022).

Figure 3 provides a decision architecture for prioritising AI projects. Figure 3 proposes that finance rank use cases according to business value, implementation feasibility, risk and time to measurable impact. This makes "quick wins" a portfolio concept rather than an invitation to implement trivial applications.

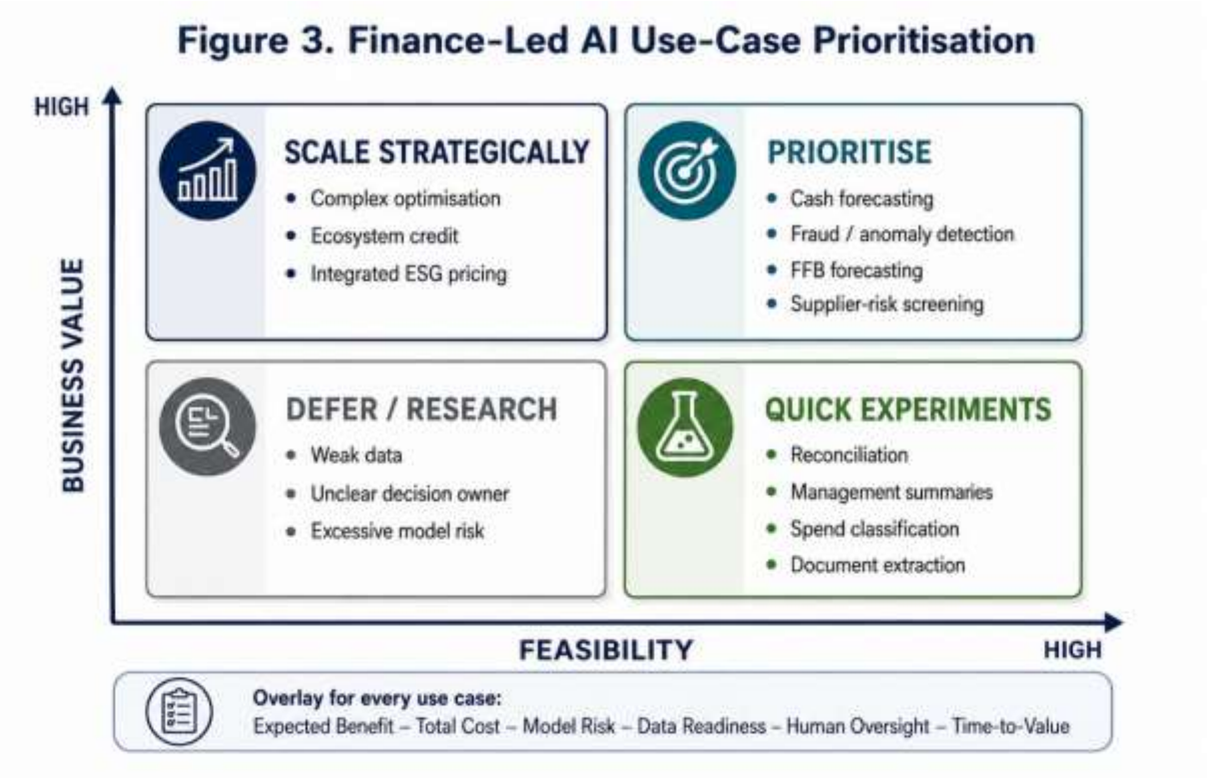

Figure 3. Finance-Led AI Use-Case Prioritisation
Source: Author synthesis.

The figure implies that an application with spectacular technical performance may still be unattractive if it influences a low-value decision, requires unavailable data or creates disproportionate governance risk. Conversely, a relatively simple model predicting short-term liquidity may create significant value if the organisation currently suffers from fragmented cash visibility.

4.9 Theme 9: Quick Wins Should Build Organizational Capability

Quick wins are useful when they create learning that enables larger transformation. Appropriate early finance applications include reconciliation automation, invoice classification, duplicate-payment detection, cash forecasting, procurement-spend analysis, management-reporting assistance and basic anomaly detection. Such applications generally have clearer historical data and limited direct impact on vulnerable external stakeholders.

However, organisations should resist a common mistake: accumulating disconnected pilots. Each successful use case should improve common infrastructure—data catalogues, access controls, model-development standards, monitoring processes and user capability. Otherwise, scaling produces duplicated data pipelines and inconsistent governance.

The auditing literature is instructive. AI adoption appears capable of improving efficiency and extending analytical coverage, but integration with professional processes determines usefulness (Fedyk et al., 2022; Almufadda and Almezeini, 2022; Rikhardsson et al., 2022). AI does not become enterprise capability simply because individual teams use AI tools.

Generative AI reinforces the point. It can rapidly create visible productivity gains in narrative reporting, document search and summarisation, but finance must distinguish productivity support from authoritative financial calculation. High-stakes outputs should remain connected to controlled systems of record, validated calculation engines and clear accountability (Dong, Stratopoulos and Wang, 2024; Zhao and Wang, 2024).

4.10 Theme 10: Sustainability Creates New Financial Information Requirements

Sustainable palm oil supply chains require decisions spanning economic, environmental and social dimensions. Adwiyah et al. (2023) apply a triple-bottom-line approach to palm oil supply-chain performance, illustrating the need for multidimensional performance management, while studies of supply-chain risk demonstrate the interconnected nature of stakeholder and operational exposures in Indonesian palm oil (Imbiri et al., 2023). ESG measurement itself can also be inconsistent: evidence from Indonesian palm oil companies shows that rating agencies may produce materially different ESG assessments despite drawing on related corporate sustainability information (Suhardjo, Akroyd and Suparman, 2024). This reinforces the need for finance functions to interrogate the provenance, materiality and comparability of sustainability data before incorporating them into capital-allocation decisions.

Finance can provide an important integrative mechanism because sustainability interventions compete for capital. Methane capture, renewable energy, biodiversity protection, fire-prevention infrastructure, smallholder support, certification and traceability each involve costs and benefits that occur over different time horizons. Conventional annual budgets may systematically underweight investments whose value arises through risk reduction or long-term resilience.

Sustainable-finance principles therefore require a more comprehensive notion of economic value. The limited integration of sustainability considerations into financing decisions documented in Indonesian plantation cases reinforces the importance of strengthening the connection between ESG evidence and credit allocation (Rosalina, Kartodiharjo and Sudjito, 2023). More recent studies show that AI can strengthen ESG analytics and sustainable-finance decision support, while also introducing new requirements for transparent metrics, model governance and responsible data use (Giudici and Wu, 2025; Elhady and Shohieb, 2025).

AI can assist by linking sustainability indicators with historical operating and financial outcomes. Yet it cannot decide the appropriate trade-off between profits, community welfare and environmental protection because this is fundamentally a governance choice. The appropriate role of AI is to make consequences more visible, not to hide normative decisions behind mathematical optimisation.

4.11 Theme 11: Implementation Barriers Are Primarily Socio-Technical

A recurring theme across AI research is that technological capability alone is insufficient. Data may be fragmented across ERP systems, spreadsheets, plantation-management applications, procurement platforms and external sources. Different plantations or subsidiaries may use inconsistent identifiers, while smallholder records may be incomplete.

The Indonesian palm oil context amplifies these problems. Smallholder plantations are difficult to map because of fragmentation and irregular boundaries, and certification frequently requires institutional support (de Vos et al., 2023; Pribadi et al., 2023). Governance systems themselves involve multiple public and private actors (Brandi, 2021; Putri et al., 2022). Consequently, AI implementation must confront institutional and informational fragmentation before sophisticated modelling can produce reliable results.

Another barrier is skills. Finance professionals require greater understanding of data, probability, model limitations and AI governance, while technologists require deeper knowledge of accounting, controls, sustainability and plantation economics. Cross-functional teams therefore matter more than isolated data-science units.

Cybersecurity and confidentiality are additional concerns. Financial information, farmer identities, location data and commercial supply-chain data can be sensitive. Generative-AI tools intensify the risk that confidential information may be entered into uncontrolled environments. Responsible AI therefore requires role-based access, data minimisation, approved toolsets, logging and security monitoring.

Finally, organisational incentives may undermine technically sound solutions. Managers whose performance is judged by short-term cost reductions may resist sustainability investments; business units may be reluctant to share data; procurement may prioritise price while sustainability teams prioritise compliance. AI cannot resolve these incentive conflicts. Finance leadership must align measurement and accountability.

5. DISCUSSION AND ANALYSIS

5.1 Finance as the Orchestration Layer

The thematic synthesis suggests that finance occupies a distinctive position in the AI-enabled palm oil enterprise. It has access to transaction information, participates in planning, evaluates investments, manages liquidity, oversees risk and communicates performance to senior management and investors. This places finance at the intersection of operating evidence and resource allocation.

The proposed role can be described as **AI-enabled strategic intelligence**. Strategic intelligence differs from conventional reporting in four respects. It is forward-looking rather than primarily historical; it combines financial and non-financial information; it explicitly models uncertainty; and it is connected to decision rights. The objective is not to maximise the number of AI models but to increase the quality and timeliness of economically consequential decisions.

Dynamic-capability theory helps explain why. AI can strengthen organisational sensing by identifying emerging risks or opportunities. Finance participates in seizing those opportunities through capital allocation, financing and budgeting. Organizational redesign, data standardisation and governance constitute part of the transforming capability required to make AI durable. Evidence linking AI capability and firm performance, as well as AI and more efficient financial asset allocation, supports this interpretation (Mikalef and Gupta, 2021; Li, Zhong and Tong, 2024).

This perspective also modifies the traditional CFO agenda. AI investment should not be evaluated only by finance; finance itself must become one of the principal domains being transformed. The CFO becomes both the evaluator of AI investments and an accountable user of AI.

5.2 Five Critical Trade-offs

The first trade-off is **efficiency versus inclusion**. Digitised suppliers are easier to assess and monitor, but prioritising only data-rich suppliers can systematically disadvantage smallholders. Sustainable AI must deliberately avoid equating visibility with legitimacy.

The second is predictive accuracy versus explainability. More complex models may improve prediction, but consequential financial decisions require explanations that can be communicated to boards, auditors, lenders, regulators and affected stakeholders. Finance research increasingly treats explainability and trustworthiness as core requirements rather than secondary features (Bussmann et al., 2021; Fritz-Morgenthal, Hein and Papenbrock, 2022; Giudici and Raffinetti, 2023).

The third is automation versus judgement. Transactional automation can be extensive, but investment, supplier exclusion, credit and sustainability decisions involve context and accountability. Research on human–AI collabouration indicates that poorly designed delegation can reduce rather than improve decision quality (Fügener et al., 2022).

The fourth is **traceability versus cost and privacy**. More granular data can improve verification but also increase collection costs, surveillance concerns and cybersecurity exposure. Data should therefore be proportional to the legitimate decision purpose.

The fifth is **short-term ROI versus long-term resilience**. AI investments that improve sustainability risk management may not deliver immediate accounting savings but can preserve future market access or reduce severe tail risks. Finance requires valuation practices that recognise such asymmetry without turning speculative benefits into exaggerated business cases.

5.3 An Integrated AI-Enabled Sustainable Finance Framework

The review proposes four interconnected pillars that together connect operational efficiency, predictive capability, sustainable capital allocation and responsible governance. These pillars are analytically distinct but mutually dependent because weaknesses in one can constrain the value created by the others.

The first is **intelligent financial operations**. This includes reconciliation, transaction classification, continuous controls, anomaly detection and automated reporting. Its purpose is to create reliable, timely financial information and release professional capacity from repetitive work.

The second is **predictive financial intelligence**. This includes FP&A, yield-linked forecasting, liquidity prediction, commodity-price scenarios, counterparty analysis and enterprise risk analytics. This pillar moves finance from explaining outcomes to anticipating them.

The third is **sustainable capital and supply-chain finance**. It connects finance with replanting, smallholder credit, certification support, traceability, sustainability-linked finance, capital expenditure and ESG risk.

The fourth is responsible AI governance. It determines who owns each model, which data may be used, how models are validated, which decisions require human review, how fairness is assessed and how outputs are audited. Organizational AI-governance research demonstrates why structures, procedures and relationships need to operate together rather than relying on ethical principles alone (Mäntymäki et al., 2022; Birkstedt et al., 2023; Mökander and Floridi, 2023; Papagiannidis, Mikalef and Conboy, 2025).

5.4 Responsible AI Governance Architecture

Figure 4 translates responsible-AI principles into a finance-oriented governance architecture. The model places human accountability at the top rather than inside the technology layer because the ultimate responsibility for financial decisions cannot be delegated to a model.

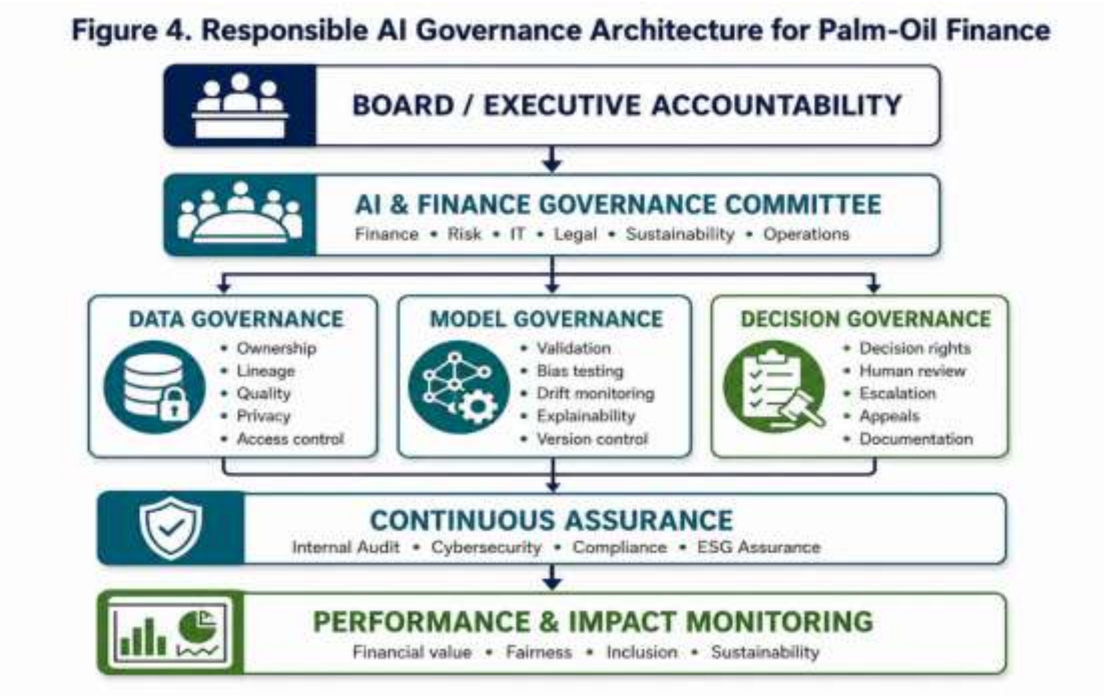

Figure 4. Responsible AI Governance Architecture for Palm-Oil Finance

Source: Author synthesis based on Mäntymäki et al. (2022), Mökander and Floridi (2023), Kluge Corrêa et al. (2023), Hadley, Blatecky and Comfort (2025) and Papagiannidis, Mikalef and Conboy (2025).

Figure 4 suggests that AI governance should be proportionate to impact. A model assisting expense categorisation does not require the same oversight as a model influencing smallholder credit, supplier exclusion or major investment decisions. Organizations can use risk tiers based on financial magnitude, stakeholder impact, reversibility, regulatory exposure and degree of automation.

5.5 A Staged Implementation Roadmap

Transformation should proceed in stages rather than attempting an enterprise-wide AI overhaul. A staged approach allows the organisation to build data quality, governance routines and user capability before granting AI systems greater influence over high-impact financial decisions.

Stage 1: establish finance-data readiness. Organizations should map financial, agronomic, supplier, geospatial, and sustainability data; establish common identifiers; define ownership; improve master data; and document quality limitations.

Stage 2: pursue controlled quick wins. Reconciliation, payment anomalies, short-term cash forecasting, document extraction, and management-reporting assistance can demonstrate value while creating governance routines.

Stage 3: build predictive finance. Organizations can extend into FFB forecasting, margin prediction, liquidity scenarios, supplier risk, and procurement analytics.

Stage 4: create cross-functional decision intelligence. Finance, operations, procurement and sustainability data should be combined to inform replanting, capital expenditure, supplier intervention and sustainability investment.

Stage 5: move toward ecosystem intelligence. Mature systems can integrate cooperatives, financiers, suppliers, mills, certification information and buyers where legitimate data-sharing arrangements exist.

Stage 6: institutionalise continuous responsible-AI governance. Model monitoring, data-quality reviews, independent validation, cybersecurity, fairness evaluation and business-value measurement become ongoing processes. This sequence is shown in Figure 5. Figure 5 emphasises that organisational maturity should precede increasing AI decision authority. High-impact automation should not be implemented merely because the algorithm is technically available.

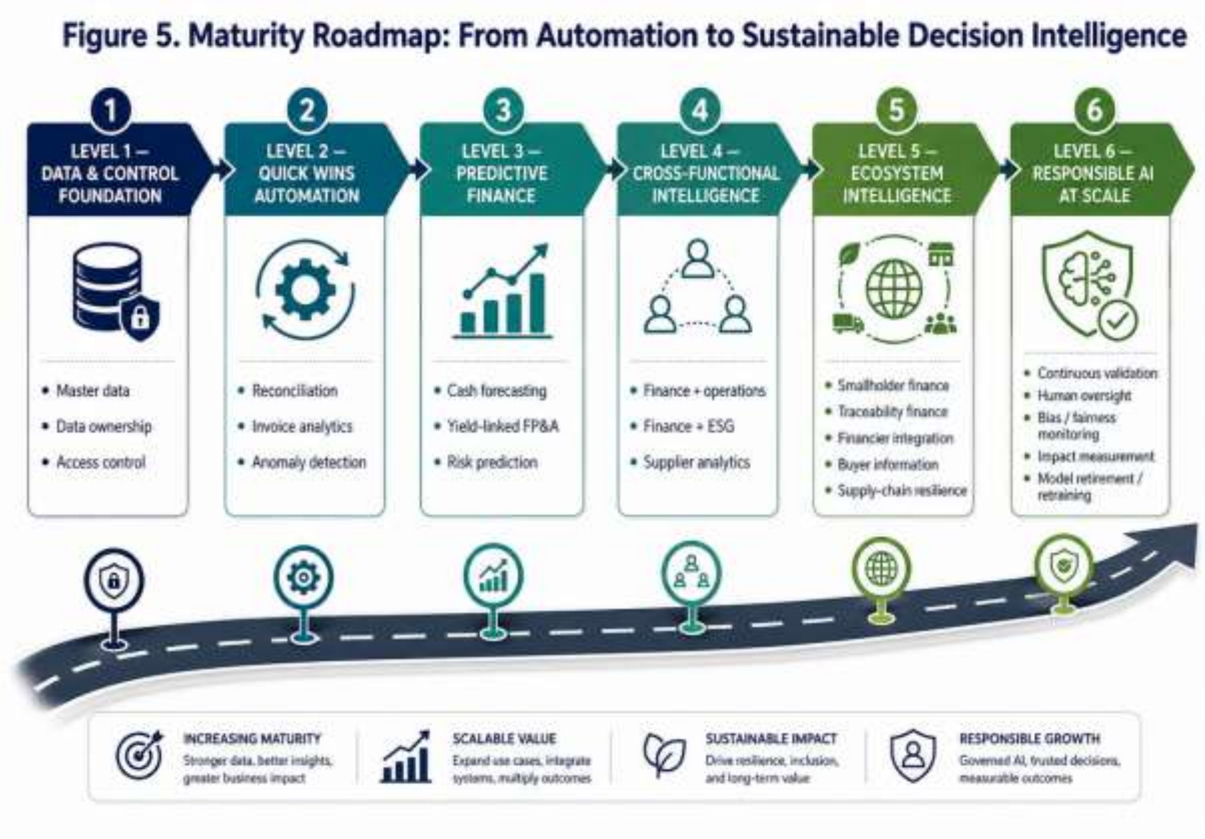

Figure 5. Maturity Roadmap: From Automation to Sustainable Decision Intelligence
Source: Author synthesis.

The roadmap makes clear that AI maturity is not defined by the number of models. A company with a few well-governed models connected to important decisions may be more mature than a company operating dozens of experimental applications with weak data ownership.

5.6 Implications for Smallholders and Sustainable Supply Chains

A sustainable palm oil transition that excludes smallholders is structurally fragile. Certification research consistently demonstrates that independent producers encounter greater barriers than more organised or historically supported farmers (Watts et al., 2021; de Vos et al., 2023). More recent evidence confirms that certification uptake is sensitive to the availability of training, financial incentives and farmers' risk preferences, indicating that inclusion depends on the institutional design of the transition rather than on compliance demands alone (Reich and Mußhoff, 2025). Sustainability governance also generates paradoxes when environmental requirements conflict with social inclusion or commercial incentives (Grabs and Garrett, 2023).

Finance can help address this problem if AI is used to improve risk differentiation rather than merely risk avoidance. Instead of categorising smallholders as a homogeneous high-risk segment, richer data can potentially distinguish economically viable farmers who lack conventional collateral. Supply-chain finance can then be linked to delivery relationships, agronomic support, replanting plans or cooperative membership.

Nevertheless, the cost of building the information infrastructure should not simply be transferred downstream to farmers. If downstream companies, international buyers or financial institutions obtain economic value from greater traceability, cost-sharing arrangements are defensible. This is consistent with the wider observation that certification success frequently depends on external facilitation and incentives (Apriani et al., 2020; Pramudya et al., 2022).

5.7 Implications for CFOs and Finance Leadership

For CFOs, five capabilities become increasingly important. Finance must understand data sufficiently to challenge model inputs; understand AI sufficiently to challenge model assumptions; understand operations sufficiently to interpret predictions; understand sustainability sufficiently to integrate non-financial risks into capital allocation; and retain governance authority sufficient to stop applications that create disproportionate risk.

This does not require CFOs to become machine-learning engineers. It requires a new form of financial leadership in which technological literacy complements accounting expertise. Finance professionals should be capable of asking whether training data represent the current business, whether model error is economically material, whether false positives have unequal impacts, whether the prediction is actionable, and whether implementation creates value after full lifecycle costs.

AI also changes talent requirements inside finance. Routine processing is likely to decline relative to analytical interpretation, scenario design, data governance and business partnering. Digitalisation research already anticipates changing controller and management-accounting roles, while audit evidence shows AI can augment analytical tasks (Möller, Schäffer and Verbeeten, 2020; Fedyk et al., 2022). The growing exposure of finance occupations to generative AI further suggests that professional advantage will increasingly depend on the ability to combine financial expertise with judgement about AI outputs, data quality and model limitations (Eisfeldt and Schubert, 2025).

5.8 Policy and Institutional Implications

Individual companies cannot solve every data and financing constraint because portions of the problem are institutional. Government agencies, financiers, certification bodies, industry organisations and companies have potential roles in developing interoperable standards for farm identity, plantation mapping, legal status and sustainability information.

However, interoperability should not evolve into indiscriminate data centralisation. Farmers should have clarity about what information is collected, why it is collected, and how it affects financial and commercial decisions. Mechanisms to correct inaccurate data are especially important because errors may become amplified once data are reused across credit, procurement and sustainability systems.

The interaction of public and private certification demonstrates the importance of institutional alignment (Brandi, 2021; Choiruzzad, Tyson and Varkkey, 2021). AI infrastructure should therefore be designed to reduce rather than add another layer of incompatible standards.

5.9 Future Research Agenda

The most important research gap is direct empirical evidence on AI-enabled finance inside Indonesian palm oil firms. Future studies could compare conventional and AI-assisted yield-linked financial forecasts; assess whether alternative data improve smallholder credit without increasing exclusion; evaluate the economic value of remote-sensing information in procurement decisions; and quantify the ROI of traceability infrastructure.

Longitudinal research is particularly important because organisational AI benefits may emerge only after complementary investments. Researchers should examine whether early productivity gains survive as models encounter changing climate, prices and operating practices.

Another research direction concerns fairness. Credit-scoring systems should be evaluated across farm size, geography, digital connectivity, cooperative membership and certification status. Researchers should ask not only whether models predict repayment accurately, but whether data limitations systematically disadvantage particular groups.

A further agenda concerns generative AI. Research should investigate its use in FP&A, management reporting, sustainability reporting, audit documentation and knowledge retrieval while distinguishing productivity assistance from authoritative decision-making. The emerging accounting-and-finance literature identifies considerable opportunities but also unresolved methodological and governance issues, particularly around reliability, professional judgement and the division of responsibility between human experts and AI systems (Dong, Stratopoulos and Wang, 2024; Zhao and Wang, 2024; Stratopoulos and Wang, 2025).

Finally, research should develop broader measures of AI investment performance. Conventional ROI should be supplemented where appropriate by measures of risk reduction, resilience, inclusion and environmental impact. This would provide a stronger analytical bridge between AI business value and sustainable finance.

6. CONCLUSION

Artificial intelligence creates an opportunity to redefine the finance function in Indonesia's palm oil sector. Its most important contribution is unlikely to be the automation of bookkeeping alone. The larger transformation lies in finance's ability to become an organisational centre of strategic intelligence: connecting financial transactions with agronomic conditions, operational performance, supplier relationships, geospatial evidence, sustainability risks, and market information, and translating them into decisions about capital, liquidity, risk and resource allocation.

This transformation can generate benefits across financial planning, cash management, fraud detection, supplier assessment, smallholder financing, investment appraisal, traceability and sustainability management. Nevertheless, AI does not automatically produce better decisions. Poor data can generate misleading predictions; complex models can obscure accountability; digital histories can disadvantage less-connected farmers; automation can create overconfidence; and disconnected pilots can consume resources without generating durable organisational capability.

For Indonesia's palm oil industry, responsible implementation therefore requires a deliberate progression from trustworthy data and modest quick wins toward predictive finance, integrated decision intelligence and, eventually, ecosystem-level financial and sustainability orchestration. The key objective should not be maximum automation. It should be better decisions with clearer accountability.

The sustainability dimension is fundamental. Smallholders should not become collateral damage in an increasingly data-intensive supply chain. AI-enabled finance should instead be designed to reduce information asymmetry, improve access to appropriately structured capital, support replanting and certification, and make the costs and benefits of sustainability interventions more transparent. Human oversight, appeal mechanisms, fairness monitoring, and proportional data governance are therefore essential.

The resulting vision is a finance function that performs three roles simultaneously: guardian of financial integrity, architect of economically disciplined AI investment, and orchestrator of sustainable value creation. In this model, the strategic question is no longer simply how finance can adopt AI. The more consequential question is how AI-enabled finance can allocate capital, manage uncertainty, and structure incentives so that economic resilience, smallholder inclusion, responsible sourcing, and environmental sustainability become mutually reinforcing components of Indonesia's palm oil supply chain.

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