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Article

Artificial Intelligence in Supply Chain Financial Planning: Applications, Governance, and Decision Accountability, a Review of Forecasting, Cash Planning, Financing Decisions, and Human Oversight

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Abstract

Artificial intelligence (AI) is moving from operational supply chain tasks, such as routing and warehouse automation, into the financial planning layer that links physical flows to cash, working capital, and funding. This review synthesises research and practice published up to 2024 on four connected domains: demand and cost forecasting, cash and working capital planning, financing decisions (including supply chain finance and credit assessment), and the human oversight arrangements that govern AI-supported decisions. The evidence shows that machine learning methods can improve forecast accuracy where data are rich and hierarchical, but gains are uneven and depend heavily on data quality, horizon, and the presence of structural breaks. In cash planning and financing, AI is most valuable when it is coupled with optimisation and scenario analysis rather than used as a stand-alone predictor. The review argues that the binding constraint on value is increasingly governance rather than algorithmic capability. Drawing on established model risk practice, AI governance standards, and emerging regulation, it proposes a decision accountability framework that assigns decision rights according to financial materiality and reversibility, specifies documentation and explainability requirements, and defines escalation paths for human override. The paper closes with a research agenda covering prescriptive analytics under uncertainty, measurement of human and AI complementarity, and the auditability of generative AI in financial planning workflows.

Keywords: artificial intelligence; supply chain finance; demand forecasting; cash flow forecasting; working capital; model risk management; AI governance; human oversight; decision accountability

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Introduction

Supply chains are financial systems as much as physical ones. Every purchase order commits cash, every inventory buffer ties up working capital, and every payment term shifts liquidity between trading partners. Supply chain financial planning is the discipline that translates expected physical activity, such as demand, production, procurement, and logistics, into expected financial outcomes, including revenue, cost of goods, cash conversion, and funding needs. It also works in the opposite direction, using financial constraints such as liquidity limits, covenants, and cost of capital to shape operational plans (Pfohl & Gomm, 2009; Wuttke et al., 2013).

The past decade has seen rapid adoption of AI techniques across supply chain management (Baryannis et al., 2019; Toorajipour et al., 2021; Okonkwo et al., 2024c). Early applications concentrated on demand sensing, inventory optimisation, and transport planning. More recently, organisations have extended these tools into treasury and financial planning and analysis (FP&A): forecasting cash receipts and disbursements, predicting supplier and customer payment behaviour, pricing early payment programmes, and recommending financing choices (Lawal & Oduleye, 2019; Medon & Oduleye, 2024). The arrival of large language models in 2023 and 2024 added a further layer, with natural language interfaces now being embedded in planning platforms to summarise variances, generate narrative commentary, and answer ad hoc queries. Integrated frameworks that combine AI and predictive analytics across supply chain functions (Rukh et al., 2024) illustrate how far this convergence has progressed. Earlier work had already argued that data science and big data analytics would reshape supply chain design and management (Waller & Fawcett, 2013; Wang et al., 2016), and survey evidence links the adoption of predictive analytics to supply chain and organisational performance (Gunasekaran et al., 2017). Generative AI has since been mapped onto specific supply chain and operations capabilities (Jackson et al., 2024).

This expansion raises a distinct set of questions. Forecasts that drive financial commitments carry direct monetary consequences, may be relied on by lenders and auditors, and can fall within regulated activities. When an algorithm recommends drawing on a credit facility, extending payment terms to a supplier, or approving trade credit for a distributor, someone must be accountable for that decision. Existing studies of AI in supply chains tend to focus on predictive accuracy, while governance literature tends to treat AI generically. Recent conceptual work on algorithmic accountability and model risk in financial services (Ominyi & Anichukwueze, 2023) and on responsible AI governance for automated decision systems (Ominyi & Anichukwueze, 2024) points toward this need, but few reviews connect prediction and governance at the level of supply chain financial planning decisions.

This review addresses that gap by synthesising research on AI across three planning domains (forecasting, cash and working capital planning, and financing decisions) and examining the governance and oversight arrangements under which AI-supported decisions are made. The study departs from earlier reviews in two respects. First, it treats the financial consequences of supply chain AI, rather than operational accuracy, as the unit of analysis. Second, it links the application evidence to model risk management, AI governance standards, and behavioural research on human oversight, and from this synthesis derives a decision rights matrix that allocates oversight by financial materiality and reversibility. The remainder of the paper describes the methodology, presents the literature synthesis, sets out a conceptual model, and then discusses the findings, their implications, the limitations of the review, and directions for future research.

Methodology

The paper adopts a narrative, integrative review design. This approach suits a topic that spans operations research, finance, information systems, and regulation, where a narrow systematic protocol limited to a single database or keyword string would miss relevant work. Sources were identified through searches of Scopus, Web of Science, and Google Scholar using combinations of terms including “artificial intelligence”, “machine learning”, “supply chain finance”, “demand forecasting”, “cash flow forecasting”, “working capital”, “trade credit”, “explainability”, “model risk”, and “human oversight”. Backward and forward citation tracking from highly cited reviews supplemented the database searches. The review also drew on a curated seed list of recent studies on financial analytics,

procurement, supply chain governance, and AI accountability, many published in journals with an emerging-market focus, to ensure that work from Africa and other developing regions was represented. The final corpus comprises 200 sources: 100 drawn from the seed list and 100 identified through database searching and verified against publisher or DOI records. Recent reviews note that AI tools can assist the synthesis of literature and stakeholder data in operations research (Obukadata et al., 2024), but such tools still require human verification of sources. Inclusion criteria were: (a) peer-reviewed articles, books, and conference papers, or authoritative standards and regulatory documents; (b) explicit attention to forecasting, liquidity, working capital, financing, or the governance of algorithmic decisions; and (c) publication up to and including 2024. Practitioner reports were consulted for context but are not relied on for empirical claims. The synthesis is thematic, organised around the four domains named in the title, with attention to where evidence is strong, where it is mixed, and where it is largely absent.

Literature Synthesis

This section synthesises the literature in six parts: the conceptual background, followed by AI applications in forecasting, cash and working capital planning, and financing decisions, and then the governance and human oversight literature that conditions how those applications become decisions.

Conceptual background

Supply chain financial planning

Supply chain financial planning sits at the intersection of sales and operations planning (S&OP), integrated business planning, and treasury management (Dada et al., 2021a; Lawal & Oduleye, 2021b). Its core outputs are a demand-driven revenue forecast, a cost and margin forecast, a cash flow forecast at weekly or monthly granularity, and a funding plan. The cash conversion cycle, defined as days inventory outstanding plus days sales outstanding minus days payables outstanding, is the summary metric that links these outputs. Empirical studies link shorter cash conversion cycles to higher profitability in SMEs (García-Teruel & Martínez-Solano, 2007) and to better financial performance in manufacturing (Kroes & Manikas, 2014), although the relationship between working capital and performance is inverted U-shaped rather than linear (Aktas et al., 2015; Baños-Caballero et al., 2014). Hofmann and Kotzab (2010) caution that one firm's reduction in its cycle often shifts costs onto its trading partners, which is why a supply chain view is needed. Supply chain finance (SCF) extends this view beyond the firm, treating the financing of goods in transit, receivables, and payables as a collaborative problem across trading partners (Hofmann & Belin, 2011; Gelsomino et al., 2016).

Operations research has long shown that operational and financial decisions interact. Buzacott and Zhang (2004) demonstrated that asset-based financing constraints alter optimal inventory policies, and Kouvelis and Zhao (2012) showed how the structure of trade credit contracts shapes the choice between supplier and bank financing. Later work shows that trade credit lets retailers share demand risk with suppliers (Yang & Birge, 2018), limits the incentive for bank-financed firms to overstock (Chod, 2017), and supports contract coordination even when both parties face bankruptcy costs (Kouvelis & Zhao, 2016). Finance research explains why suppliers lend at all: they can enforce repayment by threatening to cut off supply (Cuñat, 2007), their terms vary with the type of goods traded (Giannetti et al., 2011), and large, creditworthy buyers tend to obtain the longest terms (Klapper et al., 2012). These models assume known or parametrically specified demand distributions. AI changes the picture by offering richer, data-driven estimates

of the uncertain quantities, but it also introduces model uncertainty that must be governed. Planning models for sustainable profitability (Medon & Oduleye, 2023) and data-driven cost management models for strategic financial planning (Oduleye & Medon, 2021) show how these estimates are increasingly being folded into corporate planning cycles, while CFO-led strategic finance models emphasise the coordination required when supply chains span joint ventures and cross-border partners (Isiekwu et al., 2021).

Categories of AI in financial planning

For the purposes of this review, AI techniques are grouped into four categories according to the role they play in planning decisions. Predictive models which estimate future quantities such as demand, prices, lead times, payment dates, or default probabilities. Examples include gradient-boosted decision trees, random forests, recurrent and transformer-based neural networks, and probabilistic forecasting methods. Prescriptive models which recommend actions by combining predictions with optimisation, for example stochastic programming, reinforcement learning, or "predict then optimise" approaches (Bertsimas & Kallus, 2020; Elmachtoub & Grigas, 2022). Frameworks that pair predictive and prescriptive analytics in commercial planning (Rukh et al., 2023) follow the same logic. Detection and classification models which flag anomalies, fraud, or risk events in transactional and supplier data (Atakpa & Abetoh, 2022; Atakpa & Fobellah, 2023). Generative and language models which produce narrative explanations, extract information from unstructured documents such as contracts and invoices, and provide conversational access to planning data, and which increasingly operate as agents within enterprise workflows (Nwakamma et al., 2024b). Recent versions of these models can pass major accounting certification examinations (Eulerich et al., 2024).

The distinction matters for governance. Predictive outputs inform human judgement, prescriptive outputs propose decisions, and automated execution removes the human from the loop entirely. Accountability requirements rise as systems move along this continuum.

Decision accountability

Accountability in this context means that for each AI-supported decision it is possible to identify who had authority to make it, what information and model outputs were relied on, what alternatives were considered, and who must answer for the outcome. Novelli, Taddeo and Floridi (2024) distinguish accountability from related notions such as responsibility and transparency, emphasising that accountability is a relationship in which an agent must justify conduct to a forum that can impose consequences. Applied to financial planning, the forum may be senior management, the board, auditors, lenders, or regulators. Annan (2024) adds that trade secret protection for proprietary algorithms can obstruct accountability, a tension that arises whenever planning models are licensed from vendors rather than built in house.

AI in forecasting

Demand forecasting

Demand forecasting is the most mature application of AI in supply chain planning and the foundation of all downstream financial projections. Early comparative work by Carbonneau, Laframboise and Vahidov (2008) found that neural networks and support vector machines could outperform traditional methods for forecasting distorted demand signals in extended supply chains, though not uniformly. Makridakis, Spiliotis and Assimakopoulos (2018) subsequently cautioned that on many univariate series, simple statistical methods matched or exceeded more

complex machine learning approaches at lower computational cost. The M4 competition reinforced this picture: combinations and hybrids of statistical and machine learning methods performed best, while pure machine learning entries did poorly (Makridakis et al., 2020).

The M5 forecasting competition, which used hierarchical daily sales data from a large retailer, marked a turning point. Makridakis et al. (2022a) reported that the top-performing entries were dominated by LightGBM, a gradient-boosted tree method, trained as global models across many related series and incorporating explanatory variables such as prices, promotions, and calendar events. These approaches outperformed strong statistical benchmarks, particularly at lower levels of the product hierarchy. The lesson for supply chain planners is that AI adds most value where there are many related series, informative covariates, and enough history to learn cross-series patterns. The companion uncertainty track found that gradient-boosted methods also produced better-calibrated probabilistic forecasts than statistical benchmarks (Makridakis et al., 2022b). Hierarchical reconciliation methods ensure that forecasts at product, store, and total levels add up consistently (Hyndman et al., 2011; Wickramasuriya et al., 2019), including across daily, weekly, and monthly planning horizons (Athanasopoulos et al., 2017), which matters when the same forecast must serve operational and financial plans.

Studies published in emerging-market and practitioner-oriented journals report consistent patterns. Aifuwa et al. (2020) and Akin-Oluyomi et al. (2023) describe predictive analytics models that improve demand forecasting accuracy and reduce inventory inefficiencies in supply chain and e-commerce procurement settings. Tonoyan et al. (2021a) review machine learning algorithms that convert demand forecasts into revenue projections for financial planning, and Okonkwo et al. (2024b) extend predictive methods to procurement planning, linking forecasts of material requirements to operational uptime and spend. Together these studies reinforce the view that demand forecasts are most useful to finance when they are translated directly into revenue, cost, and purchasing commitments. Supply chain analytics frameworks aimed at improving forecasting accuracy and reducing operational bottlenecks (Akin-Oluyomi & Akhigbe, 2023) and CRM-based sales forecasting models in lending institutions (Dada et al., 2021b) show that the same techniques are being applied across retail, manufacturing, and financial services.

Deep learning architectures have extended these capabilities. DeepAR (Salinas et al., 2020) produces probabilistic forecasts from autoregressive recurrent networks trained across large collections of series, and the Temporal Fusion Transformer (Lim et al., 2021) combines multi-horizon forecasting with attention mechanisms that offer a degree of interpretability. Probabilistic outputs are especially important for financial planning because cash and funding decisions depend on the tails of the distribution, not only on point estimates. In retail settings, machine learning forecasts demand on holidays and other special days more accurately than time series methods (Huber & Stuckenschmidt, 2020), meta-learning can combine base forecasters effectively (Ma & Fildes, 2021), and pairing tree-based demand forecasts with price optimisation raised revenue in a field experiment (Ferreira et al., 2016).

Evidence on retail and consumer goods forecasting reviewed by Fildes, Ma and Kolassa (2022) confirms that machine learning gains are context dependent. They are larger for promotional and intermittent demand, smaller for stable high-volume items, and can disappear when data quality is poor or when the future departs sharply from the training period. The COVID-19 pandemic illustrated this last point vividly: many models trained on pre-2020 data failed during the demand shocks of 2020 and 2021, and organisations relied heavily on human judgement and scenario planning during that period. Syntetos et al. (2016) also note a persistent gap between the forecasting methods developed by researchers and those used in companies, suggesting that adoption barriers matter as much as accuracy.

Cost, price, and lead time forecasting

Financial planning also requires forecasts of input costs, commodity prices, freight rates, exchange rates, and supplier lead times. Machine learning has been applied to each of these, often drawing on external data such as market indices, shipping data, and news sentiment. These forecasts feed directly into margin projections and inventory valuation. Their accuracy is typically lower than that of demand forecasts because the underlying series are driven by macroeconomic and geopolitical factors that are difficult to anticipate. Predictive models for vendor risk assessment and procurement cost optimisation (Tonoyan et al., 2024a) and digital supply chain models for cost control (Okonkwo et al., 2024c) illustrate the current direction of work, as do machine learning models for predictive cost optimisation (Tonoyan et al., 2022b), data-led cost governance (Adesuyi et al., 2023), and variance analytics for cost control in manufacturing (Aliliele et al., 2024), supported by big data and business intelligence in procurement (Akinleye et al., 2023). Here AI is more useful for monitoring and early warning, such as detecting emerging supply disruptions, than for precise point prediction (Baryannis et al., 2019).

Judgemental adjustment and forecast value added

In practice, statistical and machine learning forecasts are routinely adjusted by planners. Fildes et al. (2009) found that judgemental adjustments in supply chain companies were frequent, that small adjustments tended to reduce accuracy, and that larger downward adjustments were more beneficial than upward ones, which were often driven by optimism. Earlier reviews reached similar conclusions, finding that judgement adds value mainly when forecasters hold information the model lacks (Lawrence et al., 2006), and that forecasters discount identical advice more when told it comes from a statistical method rather than a human expert (Önkal et al., 2009). This finding remains central to the governance of AI forecasts: human override is not automatically a safeguard and can itself be a source of bias. Forecast value added analysis, which measures whether each step in the forecasting process improves accuracy relative to a naive benchmark, provides a practical way to evaluate both algorithmic and human contributions. Standardising reporting and decision workflows (Alieme et al., 2022) makes such measurement possible, because overrides are recorded consistently rather than buried in spreadsheets.

AI in cash and working capital planning

Cash flow forecasting

Cash flow forecasting translates operational plans into the timing of receipts and payments. Traditional approaches rely on the direct method, which aggregates expected receipts and disbursements, or the indirect method, which derives cash flow from projected financial statements. Both depend heavily on assumptions about payment timing. AI contributes by learning payment behaviour at the level of individual customers and invoices, using features such as invoice size, customer history, seasonality, and dispute status.

Comparative studies suggest that machine learning can improve short-term cash forecasting. Weytjens, Lohmann and Kleinsteuber (2021) compared multilayer perceptrons and long short-term memory networks with ARIMA and Prophet for cash flow prediction and found that the neural approaches performed better on their data. However, the literature on cash flow forecasting with AI remains thinner than that on demand forecasting, much of it is based on single-firm datasets, and results are difficult to generalise. Treasury practitioners have noted that the largest accuracy improvements often come from better data integration, such as linking enterprise resource planning (ERP) records with bank statement data, rather than from algorithm choice alone, a point echoed in reviews of

integrated data management for financial forecasting (Agu et al., 2023b) and in work showing that poor data quality undermines supply chain analytics more generally (Hazen et al., 2014).

Several recent conceptual and review studies address the link between cash forecasting and working capital more directly. Tonoyan et al. (2021b) review predictive cash flow modelling in retail and its connection to working capital optimisation, and Oduleye and Medon (2023) propose a predictive model that ties cash flow forecasts to working capital management in corporations. Adesuyi et al. (2022) show how operational and market signals can be incorporated into predictive budgeting models. In multinational supply chains, cash forecasting also requires consolidation across entities and currencies; Dada et al. (2021a) address this through a tiered treasury architecture for cash flow consolidation and foreign exchange risk control. Automated financial consolidation models for multinational corporations (Bola-Sadipe et al., 2023) and predictive AI models for liquidity optimisation in international payment systems (Akomolafe, Olaogun, et al., 2023) address adjacent parts of the same problem. In utilities and energy distribution, integrated financial planning frameworks have been used to link revenue optimisation with operational data (Nnabueze et al., 2024). Revenue assurance approaches that use AI and big data to detect leakage (Sakyi et al., 2023) improve the reliability of the receipts side of the forecast.

Receivables and payables optimisation

Predicting when customers will pay enables more precise collections strategies. Classification and survival models can estimate the probability that an invoice will be paid late, prioritising collections effort and informing credit limit decisions. On the payables side, AI can recommend which invoices to pay early to capture discounts, which to pay on terms, and which to route through supplier finance programmes, taking into account the firm's cash position and cost of capital. These are prescriptive problems in which the prediction of payment behaviour feeds an optimisation of liquidity. Smart contract automation has been proposed for supplier payment systems and performance benchmarking (Akomolafe et al., 2022) and for resolving disputes over international supplier payments (Akomolafe et al., 2024), which would allow some payment decisions to be executed automatically once agreed conditions are met.

Inventory as working capital

Inventory is typically the largest working capital component for manufacturers and retailers. AI-driven inventory optimisation, including multi-echelon optimisation using probabilistic demand forecasts, can reduce safety stock while maintaining service levels, releasing cash. Bertsimas and Kallus (2020) showed how machine learning predictions can be integrated directly into prescriptive decision rules for inventory, and Elmachtoub and Grigas (2022) argued that models should be trained on the decision loss they induce rather than on prediction error alone. Empirical work supports this view: data-driven newsvendor models that learn order quantities directly from features outperform separate estimate-then-optimise approaches (Ban & Rudin, 2019; Huber et al., 2019), and deep learning models can be trained on newsvendor cost directly (Oroojlooyjadid et al., 2020). Embedding economic evaluation algorithms in enterprise data pipelines (Ogundairo & Ayivi-Donkor, 2023) is one practical route to measuring this financial value. For financial planning, this implies that the "best" forecast is the one that leads to the best working capital outcome, which may differ from the most accurate forecast by conventional metrics.

Scenario planning and digital twins

Supply chain digital twins, which are simulation models continuously updated with

operational data, allow planners to test the financial consequences of disruptions and policy changes. Ivanov and Dolgui (2021) describe digital twins as a means of managing disruption risk and resilience. Related studies show how digital technologies shape the ripple effect of disruptions (Ivanov et al., 2019) and how simulation can estimate the supply chain impact of epidemic outbreaks (Ivanov, 2020). When linked to financial models, they allow organisations to estimate the cash impact of scenarios such as supplier failure, port closure, or demand collapse, and to pre-arrange liquidity responses. AI contributes by generating scenarios, calibrating simulation parameters, and identifying which scenarios most threaten liquidity. Filani et al. (2023) argue that scenario-based financial modelling strengthens long-term planning decisions, and Anene (2021) reviews how supply chain risk management practices evolved after major disruptions, underlining why liquidity planning must anticipate shocks rather than extrapolate recent history. Digital twin and automation frameworks have also been applied to procurement, where they reduce errors and turnaround time (Akinlade et al., 2024), and simulation modelling has been used to assess the financial impact of process optimisation (Tonoyan et al., 2022a). Resilience indices for post-pandemic supply chains (Efobi et al., 2023) and sector studies such as pharmaceutical and critical infrastructure supply chain resilience (Awulu et al., 2022; Ogunwole et al., 2021) provide indicators that can be linked to liquidity scenarios.

AI in financing decisions

Supply chain finance programmes

Supply chain finance encompasses reverse factoring (payables finance), dynamic discounting, receivables purchase, inventory finance, and pre-shipment finance (Gelsomino et al., 2016). These instruments allow a buyer with a strong credit rating to extend payment terms while enabling suppliers to receive early payment at a financing cost linked to the buyer's risk. Models of reverse factoring show that it benefits SME suppliers most when demand is uncertain and receivable terms are long (Lekkakos & Serrano, 2016), that the gains depend on the financing cost gap and how payment terms are set (Dello Iacono et al., 2015), and that buyer intermediation can improve efficiency relative to traditional bank finance (Tunca & Zhu, 2018). AI is used to select which suppliers to onboard, to price early payment offers dynamically, to forecast programme utilisation, and to monitor supplier financial health. Agboada et al. (2018) show, from the lender side, how distributorship and trade finance products can be designed to grow bank relationships in emerging markets, which illustrates that the design of SCF instruments shapes the data available for AI-based assessment. Supplier relationship management (Ike et al., 2021) and vendor governance practices (Okonkwo et al., 2019) also determine how much information buyers hold about their suppliers.

Dynamic discounting is a natural application of prescriptive AI. The buyer uses surplus cash to pay suppliers early in exchange for a discount that varies with the number of days accelerated. Optimising this requires forecasting the buyer's cash surplus, predicting each supplier's willingness to accept a given discount, and comparing the implied return with alternative uses of cash. Platforms increasingly automate these offers, which raises questions about fairness to smaller suppliers and about disclosure of the effective interest rates involved.

Credit risk assessment in supply chains

Credit risk models determine trade credit limits for customers and eligibility of suppliers for financing. Supply chain data offer information beyond conventional financial statements, including transaction histories, order patterns, delivery performance, and the identity and strength of trading partners. Zhu et al. (2017) compared individual, ensemble, and integrated ensemble machine learning

methods for predicting the credit risk of small and medium-sized enterprises in supply chain finance and found that ensemble methods improved prediction. This is consistent with broader evidence: SME-specific default models outperform generic corporate models (Altman & Sabato, 2007), ensembles and random forests outperform logistic regression across credit scoring datasets (Lessmann et al., 2015), and ensemble methods improve bankruptcy prediction (Barboza et al., 2017). This line of work suggests AI can widen access to finance for smaller firms that lack audited accounts, a significant consideration in emerging markets where SME finance gaps are large. Okafor et al. (2021) describe how fintech-enabled transaction banking and digital lending are already expanding SME access to working capital, and Tonoyan et al. (2024a) propose predictive models for assessing vendor risk that can inform both procurement and supplier finance decisions. Related work on data-driven risk evaluation in emerging-market financial institutions (Akomolafe & Agu, 2019b), machine learning in insurance underwriting (Oluwo et al., 2024), and AI-driven risk scoring of cross-border trade payment transactions (Adesuyi et al., 2024) shows that the same modelling approaches are spreading across the financial services that support trade. Fraud detection is a closely related concern: adaptive fraud risk scoring for real-time transaction monitoring (Fadayomi et al., 2024) and predictive analytics for financial risk detection (Adelanwa et al., 2023) are relevant wherever supplier onboarding and payments are automated.

However, credit decisions are among the most heavily regulated uses of AI. Models that use relational or behavioural data may embed bias (Mehrabi et al., 2021), may be difficult to explain to applicants, and may fall within high-risk categories under emerging regulation. Explanation methods based on Shapley values can make machine learning credit models more transparent to supervisors (Bussmann et al., 2021). Where lenders rely on buyer-provided supply chain data, there are also questions about data rights and potential conflicts of interest.

Corporate funding and liquidity decisions

At the corporate level, AI-generated cash forecasts inform decisions about drawing on revolving credit facilities, issuing commercial paper, hedging currency exposures, and investing surplus cash. These decisions are typically made by treasury committees with defined authority limits, and AI serves as an input rather than a decision-maker. The key value lies in earlier and more reliable identification of funding gaps and in better quantification of uncertainty, which allows liquidity buffers to be sized more efficiently. Lawal and Oduleye (2021a) propose a decision model for capital allocation built on financial analytics, which illustrates how such forecasts can be embedded in a structured approval process rather than left to informal judgement. Similar arguments have been made for aligning capital budgeting with execution in capital-intensive sectors (Nwangwu et al., 2021).

Summary of applications

Table 1 summarises the main applications reviewed in Sections 3.2 to 3.4, the dominant techniques, the maturity of the evidence base, and the principal risks.

Governance of AI in financial planning

The role of governance

As the preceding sections show, the technical capability to produce useful forecasts and recommendations is broadly established. What limits value is the ability of organisations to trust, validate, and act on these outputs in a controlled way. Three features of financial planning make governance especially important. First, outputs flow into financial statements, lender reporting, and investor guidance, so errors can propagate into external commitments. Second, decisions such as credit extensions and funding draws are difficult or costly to reverse. Third, financial

Table 1: AI applications in supply chain financial planning

Domain	*Application*	*Typical techniques*	*Evidence maturity*	*Key risks*
Forecasting	Demand forecasting	Gradient-boosted trees, global deep learning (DeepAR, TFT), ensembles	High	Structural breaks, data quality, biased overrides
Forecasting	Cost, price and lead time forecasting	Regression ensembles, NLP on external signals	Moderate	Low predictability, spurious signals
Cash planning	Cash flow forecasting	LSTM, gradient boosting, hybrid statistical models	Low to moderate	Single-firm evidence, data integration gaps
Cash planning	Receivables and payables optimisation	Survival models, classification, optimisation	Moderate	Customer impact, fairness
Cash planning	Inventory and working capital	Prescriptive analytics, predict then optimise	Moderate to high	Misaligned objectives, service failures
Financing	Supply chain finance and dynamic discounting	Pricing optimisation, propensity models	Low to moderate	Supplier fairness, disclosure
Financing	SME and trade credit risk	Ensemble classifiers, network features	Moderate	Bias, explainability, regulation
Financing	Corporate liquidity and funding	Scenario generation, stochastic simulation	Low	Overreliance, tail risk underestimation

Note: Evidence maturity reflects the volume and generalisability of peer-reviewed empirical work up to 2024, as assessed in this review.

planning processes are already subject to internal control frameworks and audit, so AI must fit within existing accountability structures rather than bypass them. Studies of AI adoption readiness in small and medium-sized enterprises (Alieme et al., 2023) and of the gap between supply chain AI capability and actual use (Ogundairo & Ayivi-Donkor, 2024) suggest that many deployments stall precisely because these organisational conditions are not in place.

Model risk management

The most established governance tradition for quantitative models in finance is model risk management. The US Federal Reserve and Office of the Comptroller of the Currency guidance SR 11-7 (2011) defines model risk as the potential for adverse consequences from decisions based on incorrect or misused model outputs. It requires sound model development, independent validation, ongoing monitoring, and effective challenge, supported by a model inventory and clear ownership. Although written for banks, its principles translate well to corporate financial planning models: every forecasting and cash model should have an owner, documented assumptions, validation evidence, performance monitoring, and defined limitations. Ominyi and Anichukwueze (2023) review how algorithmic accountability and model risk management approaches are being adapted to machine learning in financial services, providing a bridge between this banking tradition and broader corporate use. Risk-based internal control models (Akomolafe & Agu, 2019a), AI-enabled IT general controls and SOX audit automation (Mbonu et al., 2022), and comparative reviews of SOX compliance in cross-border auditing (Agu et al., 2023a) indicate how AI-driven planning models can be brought within existing financial reporting controls. Audit firms themselves are adopting AI to automate structured tasks while retaining professional judgement (Kokina & Davenport, 2017).

Machine learning models stretch this framework in several ways. They are often retrained frequently, so validation must be continuous rather than periodic. Their behaviour can shift as input data drift. Their complexity makes conceptual soundness harder to assess. And they may be embedded in vendor platforms whose internals are not fully visible to the user. Organisations therefore need to

extend model risk practices with automated monitoring, champion and challenger testing, and contractual rights to vendor documentation.

AI-specific frameworks and standards

Several frameworks published before or during 2024 address AI governance more broadly. The NIST AI Risk Management Framework 1.0 (NIST, 2023) organises AI risk management into four functions: Govern, Map, Measure, and Manage. It emphasises characteristics of trustworthy AI including validity and reliability, safety, security and resilience, accountability and transparency, explainability and interpretability, privacy, and fairness. ISO/IEC 42001:2023 specifies requirements for an AI management system, providing a certifiable structure analogous to quality or information security management systems. Academic work has mapped a convergence of AI ethics guidelines around transparency, fairness, non-maleficence, responsibility, and privacy (Floridi et al., 2018; Jobin et al., 2019), while warning that principles alone do not ensure ethical practice without methods and accountability mechanisms to apply them (Mittelstadt, 2019; Morley et al., 2020). Organisational AI governance has been defined as the rules, practices, processes, and tools that align AI use with strategy, values, and regulation (Mäntymäki et al., 2022), yet the literature remains largely conceptual (Birkstedt et al., 2023). On accountability specifically, the ethical concerns raised by algorithms have been mapped in detail (Mittelstadt et al., 2016), firms have been argued to bear responsibility for the value-laden choices built into their algorithms (Martin, 2019), and end-to-end internal audit frameworks have been proposed to close the accountability gap before deployment (Raji et al., 2020). Model documentation practices such as model cards (Mitchell et al., 2019) offer a practical format for recording intended use, performance across conditions, and known limitations. For generative AI components, Nwakamma et al. (2024a) review LLM-as-a-judge methods for automated model evaluation and release gating, while noting the biases such automated evaluators can introduce. At the supply chain level, Okonkwo et al. (2024a) set out a conceptual framework for digital supply chain governance that situates technology controls within broader operational governance. Embedding IT risk and ISO compliance controls into supply chain digital transformation from the outset (Mbonu et al., 2020) and governance models for compliance across retail supply networks (Akin-Oluyomi & Akhigbe, 2022) are practical expressions of the same principle, as are real-time compliance pipelines that automate risk monitoring and data governance (Uchechi et al., 2022). Governance of the APIs that connect planning systems to banks and platforms (Aliliele et al., 2023) and risk-based business intelligence architectures for financial technology platforms (Mbonu et al., 2021) address the integration layer through which AI outputs reach financial decisions. Data governance and auditability practices developed for high-volume financial operations (Okwesa & Ashore-Onisemo, 2023) and continuous compliance architectures that keep control evidence audit-ready in real time (Smart & Jooda, 2023) provide the evidence trail needed to reconstruct how a model output entered a financial decision. Tiered risk classification of AI systems aligned with the NIST AI Risk Management Framework and ISO/IEC 42001 (Smart & Jooda, 2024), and deployment models that require qualified human review of generative AI outputs before they are acted on (Jooda & Smart, 2024), offer templates for scaling oversight to the consequences of each planning decision.

Regulatory developments

The European Union Artificial Intelligence Act, Regulation (EU) 2024/1689, entered into force on 1 August 2024 with obligations phased in over the following years. It adopts a risk-based approach. Of particular relevance to supply chain finance, AI systems used to evaluate the creditworthiness of natural persons or

establish their credit score are classified as high risk, triggering requirements for risk management, data governance, technical documentation, record keeping, transparency, human oversight, and accuracy and robustness. Most business-to-business forecasting and cash planning applications are unlikely to be high risk under the Act, but organisations that extend credit to sole traders or individuals, or that operate consumer-facing financing, may be affected. Ominyi et al. (2024b) review organisational readiness for the Act among multinational enterprises. Legal analyses of the draft Act raised concerns about its reliance on self-assessment and harmonised standards (Veale & Zuiderveen Borgesius, 2021). The Act also contains transparency obligations for general-purpose AI models, which are relevant where generative AI is embedded in planning tools.

Beyond the EU, financial regulators in several jurisdictions issued guidance or discussion papers on AI in financial services during this period, and data protection laws, including the General Data Protection Regulation and Nigeria's Data Protection Act 2023, constrain how personal data may be used in automated decisions (Annan, 2022; Ominyi & Anichukwueze, 2022). Firms operating global supply chains therefore face a patchwork of requirements and benefit from adopting a common internal standard that meets the strictest applicable regime, consistent with arguments for shared responsibility and multi-jurisdictional alignment in global supply chain governance (Ominyi et al., 2021). In the banking systems that finance supply chains, harmonising risk governance with technology infrastructure and compliance frameworks is a parallel concern (Okafor et al., 2024), and AI is also being applied in customs administration and trade facilitation (Jones & Ominyi, 2024), which affects the timing of cross-border cash flows. Export controls and sanctions shape technology transfer along supply chains (Jones & Ominyi, 2023), and payment products must be redesigned as cross-border regulation changes (Olaogun et al., 2023).

Human oversight and decision accountability

The behavioural evidence

Human oversight is frequently presented as the remedy for AI risk, but behavioural research shows that the human and AI relationship is complex. Dietvorst, Simmons and Massey (2015) documented algorithm aversion: people lose confidence in algorithms more quickly than in human forecasters after seeing them err, even when the algorithm is more accurate overall. Follow-up work found that allowing people to modify algorithmic forecasts, even slightly, substantially increased

Table 2: Mapping governance instruments to supply chain financial planning

Instrument	*Primary focus*	*Implications for supply chain financial planning*
SR 11-7 (2011)	Model risk management in banking	Model inventory, independent validation, effective challenge and ongoing monitoring for forecasting and cash models
NIST AI RMF 1.0 (2023)	Voluntary AI risk management	Govern, Map, Measure and Manage functions; trustworthiness characteristics as evaluation criteria
ISO/IEC 42001:2023	Certifiable AI management system	Organisational policies, roles, risk assessment and continual improvement for AI used in planning
EU AI Act (2024/1689)	Risk-based regulation	High-risk obligations for creditworthiness assessment of natural persons; transparency for general-purpose AI
Data protection law (e.g. GDPR, NDPA 2023)	Personal data and automated decisions	Lawful basis, data minimisation and rights relating to automated decision-making in credit and collections
Model cards and documentation	Transparency practice	Standardised record of intended use, performance and limitations for each planning model

their willingness to use them (Dietvorst et al., 2018), and that a single bad piece of advice reduces reliance on automated advisors more than on human ones (Prahl & Van Swol, 2017). Burton et al. (2020) group the causes of algorithm aversion into expectations, decision autonomy, incentives, cognitive compatibility, and the design of the decision environment. Conversely, Logg, Minson and Moore (2019) found algorithm appreciation in many settings, with lay people giving more weight to algorithmic than human advice. Parasuraman and Manzey (2010) describe automation complacency and automation bias, in which operators fail to monitor automated systems adequately or follow their recommendations even when contrary information is available. Reviews of trust in automation (Hoff & Bashir, 2015) and in AI (Glikson & Woolley, 2020) identify transparency, reliability, and the way the system is presented as key influences, and automation bias is well documented in other high-stakes decision support settings (Goddard et al., 2012). These findings imply that oversight design must guard against both under-reliance and over-reliance. The forecasting evidence reviewed in Section 3.2.3 adds a further dimension: human adjustments can be systematically biased, for example by optimism or by incentives tied to sales targets. Effective oversight therefore depends on measuring whether human interventions add value, not merely on ensuring that they occur. Concerns that heavy reliance on generative AI can erode critical thinking (Adams, 2023) reinforce the need to keep planners actively engaged with the reasoning behind model outputs. Behavioural financial analytics offers a lens for explaining how such human factors shape enterprise performance (Lawal & Oduleye, 2023). Evidence on human and AI teams is mixed. Machine predictions can expose systematic errors in expert human decisions (Kleinberg et al., 2018), but explanations can increase acceptance of AI recommendations whether they are right or wrong (Bansal et al., 2021), and AI advice can make human judgements more uniform, eroding the benefit of diverse views (Fügener et al., 2021). Professionals gain most when they actively interrogate opaque AI outputs against their own expertise (Lebovitz et al., 2022).

Augmentation versus automation

Raisch and Krakowski (2021) describe an automation and augmentation paradox in management: organisations seek efficiency through automation, but the most valuable uses of AI often involve close human and machine collaboration, and the two cannot be cleanly separated over time. Jarrahi (2018) similarly argues for a symbiosis in which AI handles analytical complexity while humans contribute intuitive and holistic judgement. Shrestha, Ben-Menahem and von Krogh (2019) propose that the appropriate structure for organisational decision-making depends on factors such as the specificity of the decision search space, the interpretability of the decision process, the size of the alternative set, the speed required, and replicability. Applied to supply chain financial planning, high-volume, low-value, reversible decisions such as invoice-level payment timing are good candidates for automation, while low-volume, high-value, irreversible decisions such as major financing commitments call for AI to augment rather than replace human judgement. Governance structures proposed for automated decision systems in regulated industries (Ominyi & Anichukwueze, 2024) support this graduated approach. The human-in-the-loop machine learning literature (Ladapo et al., 2022) and recent work on human-centred automation with generative AI (Ladapo et al., 2024) offer design patterns for deciding where human review adds most value. Comparative studies of AI governance in healthcare management stress the role of executive oversight and clear accountability structures (Afrihyia et al., 2024), lessons that transfer readily to financial planning. Employee readiness for technology adoption (Akhigbe et al., 2024) is a further precondition, since oversight is only effective when reviewers understand the tools they are supervising.

Explainability

Explainability methods such as LIME (Ribeiro et al., 2016) and SHAP (Lundberg & Lee, 2017) attribute model outputs to input features, allowing users to see which factors drove a forecast or a credit score. In financial planning, explanations serve several audiences: planners who need to judge whether a forecast is plausible, managers who must approve decisions, auditors who need to verify controls, and counterparties such as suppliers or credit applicants who may be entitled to reasons for adverse decisions. Doshi-Velez and Kim (2017) caution that interpretability must be evaluated relative to the task and the user. Surveys classify the main families of explanation methods (Barredo Arrieta et al., 2020; Guidotti et al., 2018), while Rudin (2019) argues that post-hoc explanations of black-box models can mislead and that inherently interpretable models should be preferred for high-stakes decisions. A feature attribution chart may satisfy a data scientist but be meaningless to a treasury committee. Explanations should therefore be designed for the decision they support, and narrative explanations generated by language models must themselves be checked for accuracy. Performance dashboards (Ezeako et al., 2024), data visualisation for procurement decisions (Babatope et al., 2023), and real-time risk assessment dashboards in supply chains (Filani et al., 2022) show how explanations and monitoring can be presented to managers in usable form.

Allocation of decision rights

Accountability is clearest when decision rights are allocated explicitly. Table 3 proposes a decision rights matrix that assigns oversight levels according to two dimensions: financial materiality and reversibility. Organisations would calibrate the thresholds to their own size and risk appetite. At Level 4, the quality of committee deliberation matters as much as the model; inclusive leadership practices can strengthen investment committee decision-making (Oguntegbe et al., 2023).

Documentation and auditability

For each AI-supported decision at Levels 2 to 4, organisations should retain a decision record containing: the model version and data snapshot used, the output and its uncertainty range, any explanation presented to the decision-maker, the final decision, the identity of the approver, and the rationale for any override. This record serves internal audit, external audit, and regulatory inspection. It also creates the dataset needed to evaluate forecast value added and to learn whether human interventions improve outcomes over time. Such records also support technology-enabled and risk-based internal audit (Akomolafe & Agu,

Table 3: Decision rights matrix for AI-supported financial planning decisions

Oversight level	*Decision characteristics*	*Illustrative decisions*	*Accountability requirements*
Level 1: Automated with monitoring	Low value, high volume, easily reversed	Invoice-level payment scheduling within policy; routine replenishment orders	Policy limits coded into the system; exception reporting; periodic sampling review by process owner
Level 2: Human on the loop	Moderate value, reversible at some cost	Weekly cash forecast publication; dynamic discount offers within approved bands	Named reviewer with authority to halt; drift and accuracy dashboards; documented overrides
Level 3: Human in the loop	Material value or external impact	Trade credit limits; supplier onboarding to SCF programme; inventory policy changes	Explicit human approval; explanation of key drivers; record of model output and final decision
Level 4: Human decision, AI advisory	High value, hard to reverse, strategic or regulated	Drawing major facilities; covenant forecasts to lenders; credit decisions on individuals	Committee approval; independent validation of models used; scenario analysis; full audit trail

2018; Akomolafe, Agu, et al., 2023), and can feed real-time performance monitoring of planning processes (Tonoyan et al., 2024b). Tamper-proof recordkeeping architectures (Anichukwueze et al., 2021) and AI-assisted compliance monitoring with anomaly detection (Ominyi et al., 2024a) can strengthen the integrity of these records, while KPI frameworks designed for accountability (Sakyi et al., 2022) help connect decision records to performance outcomes. Reconciliation controls and redesigned financial workflows (Dogbatsey et al., 2019), structured corrective action planning after audit findings (Ebhojie et al., 2023), and cross-functional KPI frameworks (Seyi-Lande et al., 2022) complete the assurance loop. Where generative AI produces narrative commentary in planning reports, the source data and prompts should be retained so that statements can be traced and verified.

Conceptual Model

Building on the synthesis, this paper proposes a layered conceptual model of AI-supported supply chain financial planning (Figure 1). The model is intended to connect the application evidence with the governance and oversight literature, and to show where accountability attaches as model outputs move toward financial decisions.

At the base of such a system sits the data foundation: integrated, reconciled data linking operational records (orders, shipments, inventory) with financial records (invoices, payments, bank balances) and external signals, with data lineage and quality controls as prerequisites for everything above (Agu et al., 2023b; Nnabueze et al., 2021; Okoruwa et al., 2024). Above it, predictive models supply probabilistic forecasts of demand, costs, payment timing, and credit risk, with documented performance against simple benchmarks and monitoring for drift. Prescriptive and scenario models then translate those forecasts into recommended inventory, payment, and financing actions, and are trained or evaluated on decision outcomes rather than prediction error alone. The fourth layer concerns decision governance: the allocation of decision rights by materiality and reversibility (Table 3), explanation tailored to each decision audience, and defined escalation and override procedures. The final layer provides assurance and learning through a model inventory, independent validation, integrated governance for financial resilience (Akomolafe & Agu, 2019c), decision records, forecast value added analysis, and periodic review against applicable standards and regulations, feeding improvements back into the lower layers (Akomolafe, Agu, et al., 2023; Tonoyan et al., 2024b).

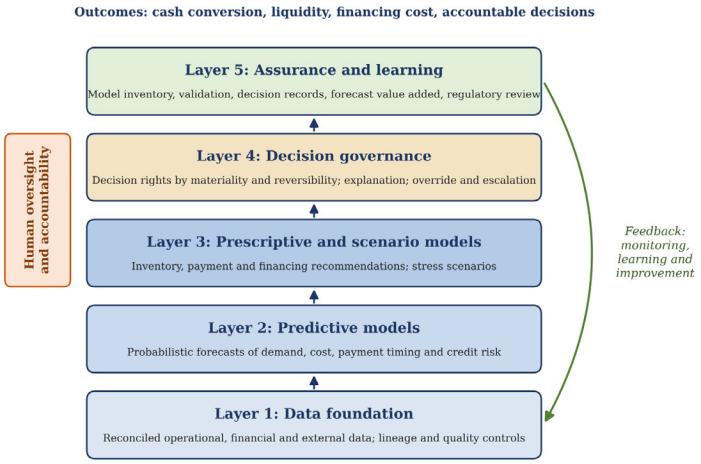


Figure 1: Layered conceptual model of AI-supported supply chain financial planning

This layered view emphasises that governance is not a separate compliance overlay but an integral part of the planning architecture. Each layer produces evidence used by the layer above, and the assurance layer closes the loop by testing whether the system as a whole, including its human participants, improves financial outcomes.

Human oversight and accountability act most strongly on Layers 3 and 4, where recommendations become commitments. The intensity of that oversight is set by the decision rights matrix in Table 3, so that routine, reversible decisions can be automated within policy limits while material, irreversible decisions remain with accountable humans who are supported, rather than replaced, by AI.

Discussion

The evidence reviewed in Section 3 points to a consistent pattern. Gains from AI are best documented where data are rich and hierarchical, as in retail demand forecasting, and are thinner and more context dependent in cash flow forecasting and financing decisions. In every domain, the binding constraints are data quality, the alignment of models with financial objectives, and the governance of how outputs become decisions, rather than the choice of algorithm. Read together, these findings suggest that AI in supply chain financial planning is best understood as a layered system rather than a set of separate tools.

Three tensions run through the evidence. The first lies between accuracy and value. Much of the forecasting literature evaluates models by statistical error, whereas the financial planning literature shows that value depends on how forecasts feed decisions about inventory, payment timing, and funding. Decision-focused approaches narrow this gap, but they are not yet standard in practice, and few studies report the cash or financing consequences of improved forecasts. The second tension lies between under-reliance and over-reliance. Behavioural studies document both algorithm aversion and automation bias, and judgemental adjustments to forecasts can either add information or introduce optimism. Oversight that simply requires human sign-off may therefore fail in either direction unless it is paired with measurement of whether interventions improve outcomes. The third tension lies between general governance frameworks and the specific character of financial planning decisions. Ethics principles, AI management system standards, and risk-based regulation provide a common vocabulary, but most supply chain planning applications fall outside the high-risk categories that attract mandatory controls. In this space, organisations rely on voluntary practice, internal audit, and model risk disciplines borrowed from banking. The synthesis suggests that these borrowed disciplines transfer reasonably well, provided that they are adapted to frequently retrained models, vendor-supplied systems, and the involvement of trading partners whose interests may diverge from those of the deploying firm. The evidence base is also uneven geographically: work from emerging markets, including Africa, is growing quickly but is largely conceptual, which limits what can be said about how AI-supported planning performs where data infrastructure and access to finance are weakest.

Implications

Theoretical implications

For research, the review suggests that supply chain AI should be studied as a socio-technical decision system rather than as a set of prediction tasks. The conceptual model in Figure 1 offers a structure for locating studies, and the decision rights matrix provides testable propositions: that the value of human oversight depends on decision materiality and reversibility, and that recorded overrides can be used to estimate whether human judgement adds or subtracts value. The review also points

to the operations-finance interface as a natural home for integrating forecasting, inventory, and financing models with the behavioural and governance literatures.

Practical implications

Several practical implications follow. Finance and supply chain leaders should register planning models in the same inventory used for other material models, assign each a named owner, and require benchmark comparisons against simple methods before outputs are relied on. Oversight effort should be concentrated where decisions are material and hard to reverse, while routine, reversible decisions can be automated within coded policy limits. Override decisions should be recorded and periodically evaluated, so that the organisation learns whether human judgement is adding or subtracting value. For lenders and platform operators in supply chain finance, explainability and fairness testing deserve particular attention because their models affect counterparties who cannot inspect them.

Policy implications

For regulators and standard setters, the main implication is that much consequential AI use in supply chains sits outside the categories that attract mandatory obligations. Guidance that clarifies how model risk principles apply to non-bank corporates, and how explainability and fairness should be assessed in supply chain finance programmes that serve small suppliers, would help close this gap. Data protection authorities have a parallel role where supplier and customer data are used to automate credit and collections decisions.

Limitations

This review has several limitations. First, much industrial AI deployment is proprietary and unpublished, so the academic literature may lag practice and over-represent successful cases. Second, the governance landscape was changing quickly during 2024, particularly following the adoption of the EU AI Act, so regulatory interpretations offered here reflect the position at the time of writing. Third, the review follows a narrative, integrative design rather than a formal systematic protocol, so the selection of sources involved judgement, and part of the corpus was drawn from a curated seed list in which conceptual studies are more common than empirical ones. Finally, the decision rights matrix and the conceptual model are derived from the literature and have not yet been tested empirically.

Future Research

Several directions for future research follow from the gaps identified. Most published evidence on AI for cash forecasting is based on single firms. Multi-firm studies using standardised benchmarks, comparable to the M-competitions in demand forecasting, would clarify when and why AI helps. Research should measure the financial value of AI forecasts, such as working capital released or financing cost avoided, rather than accuracy alone, building on predict then optimise approaches. Field studies are needed that measure whether planner overrides of AI outputs improve or degrade financial outcomes, under what conditions, and how interface and incentive design affect this. Research should examine why supply chain AI often fails to reach sustained use (Ogundairo & Ayivi-Donkor, 2024) and how readiness assessments (Alieme et al., 2023) can be adapted to finance functions.

The distributional effects of AI-driven onboarding and discount pricing on small and marginal suppliers, particularly in emerging economies, are largely unstudied. As language models are embedded in planning tools, research should examine the accuracy of AI-generated financial narratives, methods for verifying them,

and their effect on decision quality and accountability, building on emerging work on automated model evaluation and on the security of agentic AI workflows (Nwakamma et al., 2024a, 2024b). Building on readiness reviews such as Ominyi et al. (2024b), empirical studies of how firms operationalise the EU AI Act, NIST AI RMF, and ISO/IEC 42001 in non-bank financial planning contexts would inform both practice and policy. Finally, methods that detect when models are operating outside their reliable range and that trigger a shift to human-led scenario planning deserve further development, informed by the experience of 2020 to 2022.

Conclusion

AI is becoming embedded across the financial planning layer of supply chains, from demand and cost forecasting through cash and working capital planning to financing decisions. The evidence up to 2024 indicates real but uneven gains. Forecasting improvements are well documented in data-rich, hierarchical settings; cash flow and financing applications show promise but rest on a thinner evidence base. Across all domains, the value of AI depends less on algorithm selection than on data integration, alignment of models with decision objectives, and the quality of the human processes that surround them.

This review argues that governance and decision accountability are now the binding constraints on value creation. Organisations that treat AI as an input to clearly owned decisions, that calibrate oversight to financial materiality and reversibility, that document what was decided and why, and that measure whether human interventions help, are better placed to capture the benefits while managing the risks. Established model risk practices, AI governance standards, and new regulation provide the building blocks. The task for practitioners and researchers alike is to assemble them into planning systems in which the question "who decided, on what basis, and with what result" always has a clear answer.

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