DOI: 10.55643/fcaptp.5.70.2026.5327

Svitlana Kachula
D.Sc. in Economics, Professor of the Department of Finance, Banking and Insurance, Dnipro State Agrarian and Economic University, Dnipro, Ukraine;
e-mail: s.kachula@ukr.net
ORCID: 0000-0003-2540-862X
(Corresponding author)

Oleh Onopriienko
PhD in Physics and Mathematics, Associate Professor of the Department of Higher Mathematics, Physics and General Engineering Disciplines, Dnipro State Agrarian and Economic University, Dnipro, Ukraine;
ORCID: 0000-0002-3127-4616

Svitlana Khalatur
D.Sc. in Economics, Professor of the Department of Finance, Banking and Insurance, Dnipro State Agrarian and Economic University, Dnipro, Ukraine;
ORCID: 0000-0001-8331-3341

Oksana Pavlenko
Candidate of Economic Sciences, Associate Professor of the Department of Finance, Banking, and Insurance, Dnipro State Agrarian and Economic University, Dnipro, Ukraine;
ORCID: 0000-0001-6967-8424

Valentyn Bakumov
Department of Management and Law, Dnipro State Agrarian and Economic University, Dnipro, Ukraine;
ORCID: 0009-0006-9080-8864

Ilona Solodovnykova
Department of Finance, Banking, and Insurance, Dnipro State Agrarian and Economic University, Dnipro, Ukraine;
ORCID: 0000-0002-0698-8182

Received: 24/08/2026
Accepted: 22/10/2026
Published: 31/10/2026

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INTELLIGENT FINTECH ARCHITECTURE FOR LIQUIDITY MANAGEMENT IN AGRIBUSINESS ENTERPRISES: A METHODOLOGICAL APPROACH TO DIFFERENTIATING FINANCIAL DECISIONS

ABSTRACT

This study proposes a methodological approach to differentiating FinTech solutions for liquidity management in agribusiness enterprises according to their financial profile, dominant risk, and cash flow characteristics. The approach aligns an enterprise's financial diagnostics with the selection of an analytical module, forecasting horizon, liquidity buffer parameters, and level of automation in financial decision-making. An exploratory comparison of three purposively selected cases uses the official consolidated reports of MHP, Astarta and IMC for 2025, supplemented by publicly available company information on digital systems and management technologies. Cross-company comparisons use relative indicators of EBITDA cash conversion, coverage of investment outflows by operating cash flow, relative cash holdings, and debt burden. Differences in the enterprises' financial profiles are identified: the ratio of operating cash flow to EBITDA was 47.6% for MHP, 36.6% for Astarta and 75.4% for IMC; cash and cash equivalents represented 11.0%, 8.5% and 23.9% of annual revenue, respectively; and coverage of investment outflows by operating cash flow was 0.50, 0.37 and 6.54 times. The cases illustrate three potentially overlapping management profiles: investment intensity, working capital pressure and potential relative liquidity surplus. The proposed architecture links enterprise accounting, farm management and banking data to cash flow forecasts, checks of unusual payments and assessment of adverse funding scenarios. The sequence 'financial profile → dominant risk → digital analytical module → financial decision' defines the proposed contribution: explicit rules for matching financial diagnostics to the choice of tools, planning horizon and human approval procedure. Criteria are proposed for evaluating system performance, covering forecast accuracy and calibration, the frequency and magnitude of liquidity shortfalls, the cost of the liquidity buffer, the proportion of payments incorrectly blocked, the stability of model features and the completeness of the audit trail. The three cases and one reporting year do not support sector-wide generalisation or demonstrate the effectiveness of the proposed tools.

Keywords: financial technologies, artificial intelligence, agribusiness enterprise, liquidity, cash flow, FinTech, open banking, explainable artificial intelligence, CVaR, ERP, FMIS

JEL Classification: G32, G17, O33, Q12

INTRODUCTION

The financial cycle of an agribusiness enterprise is characterised by a timing mismatch between the concentration of production expenditure and the receipt of revenue. Purchases of seeds, fertilisers, crop protection products and fuel, machinery repairs, lease payments, and storage and logistics costs generate substantial cash outflows well before products are sold. The amount and timing of cash receipts, in turn, depend on yields, market prices, contractual terms, the pace of sales, logistical constraints, the timing of receivables collection and the currency composition of transactions. Consequently, a positive annual financial result does not guarantee the absence of a cash shortfall in a particular month or even week.

A conventional payment schedule partly addresses the coordination of payments, but its scope is largely limited to obligations already incurred. Such a tool does not adequately account for the non-linear effects of production and market factors on future cash flows. Weather deviations can simultaneously alter expected yields, expenditure on inputs and the timing of field operations; export delays affect inventories, receivables and foreign currency receipts; and changes in borrowing costs alter the economic rationale for the timing of financing. Liquidity management under these conditions requires a shift from recording actual balances to forecasting the range of future cash flows and assessing the cost of forecast error.

The development of FinTech provides the technical foundations for this transition. Open banking, digital payments, electronic document workflows, production management systems, automated information flows, and artificial intelligence tools can shorten the interval between information becoming available, a financial decision being made, and its execution. However, the speed of an automated transaction does not, in itself, create economic value. If a decision is based on incomplete data or an inaccurate forecast, automation merely accelerates the consequences of the error.

This gives rise to a fundamental research and practical question: how can heterogeneous production, financial, banking and market data be transformed into an integrated liquidity management system in which forecasting is linked to risk assessment, the selection of a financial action and controlled execution? The answer cannot lie in the indiscriminate implementation of the same set of digital tools across all agribusiness enterprises. Differences in cash flow structures, investment scale, debt burden, seasonality and liquidity buffers give rise to different management needs.

This study addresses how digital liquidity management tools can be differentiated according to an enterprise's financial profile. A uniform configuration of forecasting, risk and payment modules does not account for differences between enterprises whose sources of risk may include investment commitments, working capital shortages or, conversely, the inefficient retention of excess liquidity. The research problem therefore lies in formalising the relationship between an agribusiness enterprise's financial profile, its dominant liquidity risk and the configuration of FinTech tools capable of supporting an appropriate financial decision.

The focus of the study should be the economic rationale for incorporating an artificial intelligence algorithm into the FinTech architecture, rather than the individual algorithm itself. The enterprise's financial profile is proposed as the starting point for determining the dominant liquidity risk, priority analytical module, forecasting horizon, liquidity buffer parameters, and permissible level of automation.

LITERATURE REVIEW

Contemporary academic literature views FinTech primarily as a transformation of financial intermediation, infrastructure and value creation models, rather than as a collection of individual software products. Gomber, Koch and Siering classify digital finance according to technological, functional and institutional characteristics (Gomber et al., 2017). Lee and Shin establish the ecosystem nature of FinTech, in which outcomes are determined by interactions among technology companies, financial institutions, regulators and users (Lee & Shin, 2018). Ozili links the digitalisation of finance to broader access to financial services, while also highlighting the risks to stability when controls are inadequate (Ozili, 2018). These studies provide a useful classification of services and institutional relationships, but their unit of analysis is the financial ecosystem rather than a treasury rule for choosing a reserve, payment schedule, or financing limit at a specific agricultural enterprise.

The specific characteristics of the production cycle heighten the importance of FinTech for the agricultural sector. Anshari and colleagues examine digital markets, financial technologies and financing mechanisms as interconnected elements of sustainable agricultural development (Anshari et al., 2019). Hinson, Lensink and Mueller investigate the role of FinTech in transforming agribusiness and expanding financial opportunities (Hinson et al., 2019). Rayhan and colleagues systematise FinTech solutions for sustainable agricultural value chains (Rayhan et al., 2024). Recent empirical studies also demonstrate the potential of FinTech to mitigate the transmission of climate vulnerability into agricultural financial risk (Alam et al., 2025). Their strength lies in explaining financing access and agricultural value-chain relationships. For the present treasury task, a further step is needed: translating those opportunities into dated cash requirements, funding limits and approval responsibilities within an enterprise.

The development of smart farming and farm management information systems provides the information foundation for such a framework. Wolfert and colleagues identify Big Data as a core component of digital agriculture, while emphasising challenges relating to data quality, interoperability and governance (Wolfert et al., 2017). Fountas and colleagues highlight the gap between the accumulation of information in FMIS and its use in decision-making (Fountas et al., 2015). Klerkx, Jakku and Labarthe show that agricultural digitalisation changes not only technological processes but also competencies, interaction networks and the distribution of control over data (Klerkx et al., 2019). FMIS already include budgeting and

financial functions (Fountas et al., 2015). Their value is the connection to production records; the limitation for the present task is that a catalogue of system functions does not itself specify which liquidity-management configuration to select for a given financial profile.

Research into blockchain and smart contracts in food supply chains constitutes a separate strand of the literature (Kamilaris et al., 2019; Galvez et al., 2018). Their potential for financial management lies in the ability to link a verified event — delivery, product acceptance, a change in an index or fulfilment of a contractual condition — to a subsequent financial action. However, the immutability of a digital record does not eliminate the risk of an error in the original source. Automated execution must therefore incorporate verification of the source of the event, limits and a dispute resolution procedure.

Machine learning is widely used to forecast yields, prices, production parameters and other characteristics of agricultural production (Liakos et al., 2018; Kamilaris & Prenafeta-Boldú, 2018). Promising approaches for financial management include multi-horizon models (Lim et al., 2021), probabilistic forecasting (Salinas et al., 2020), methods for assessing forecast accuracy and comparing statistical and machine-learning forecasts (Hyndman & Koehler, 2006; Makridakis et al., 2018), and prescriptive analytics, which links forecasts directly to decisions (Bertsimas & Kallus, 2020). The Conditional Value-at-Risk methodology enables the assessment of the adverse tail of the distribution of financial outcomes and accounts for asymmetry in losses (Rockafellar & Uryasev, 2000). For decisions where errors are costly, Rudin (2019) argues for inherently interpretable models rather than relying only on explanations of black-box predictions. The SHAP method provides tools for assessing the contribution of individual features to a model's prediction (Lundberg et al., 2020), while comprehensive approaches to explainable AI view explainability as an element of the responsible use of artificial intelligence (Arrieta et al., 2020).

The forecasting approaches have different advantages and demands: multi-horizon and probabilistic models describe uncertainty, but require sufficiently long and reliable time series (Lim et al., 2021; Salinas et al., 2020). Forecast accuracy alone does not establish financial value. Bertsimas and Kallus (2020) already connect data and predictions to constrained decisions; Rockafellar and Uryasev (2000) provide a method for controlling adverse outcomes. These are established foundations of the proposed framework. Their application still requires enterprise-specific cost assumptions, payment constraints, and risk limits. Likewise, SHAP describes contributions to a prediction, whereas an interpretable model makes its decision rule directly available for review; neither removes the need for financial validation (Rudin, 2019; Lundberg et al., 2020).

The comparison therefore identifies an application-specific methodological task rather than an absence of forecasting, optimisation or financial functions in earlier research. Ecosystem studies explain the available services; agricultural information systems organise production data; forecasting methods estimate future cash flows; and prescriptive analytics links information to decisions. For liquidity management in agribusiness, these capabilities need to be connected through an explicit diagnostic procedure: identify the source of funding pressure, select the analytical task, align the planning horizon with payment dates, and determine the financial action and approval procedure.

The proposed contribution is this conditional mapping from an enterprise's financial profile to its liquidity-management configuration. It combines three elements: screening with comparable financial ratios, confirmation of the source of liquidity pressure using cash flow details and payment schedules, and selection of the corresponding analytical module and management response. The contribution is an integration and differentiation procedure, not a new forecasting algorithm or risk measure. The three cases illustrate its application; superiority over existing treasury practices remains a question for empirical testing.

A comparison of the reviewed research streams makes it possible to distinguish the functions already established in the literature from the additional methodological step proposed in this study. FinTech ecosystem research explains the interaction between technological and financial service providers, but does not establish enterprise-level rules for selecting liquidity management instruments. Research on digital agriculture and farm management information systems provides mechanisms for collecting and integrating production data, although the availability of such data does not automatically translate into a financial decision. Probabilistic forecasting and machine-learning methods quantify future cash flow uncertainty, while risk optimisation approaches help evaluate adverse financial outcomes. Their application, however, depends on how forecasts are connected to payment obligations, financing constraints and the enterprise's tolerance for liquidity risk. The methodological distinction of the present study lies in connecting these functions through a conditional decision procedure. Rather than introducing another forecasting algorithm or risk measure, the proposed approach specifies how financial indicators, confirmed cash flow drivers, and payment schedules can jointly determine the selection of analytical tools and the corresponding management response.

DOI: 10.55643/fcaptp.5.70.2026.5327

AIMS AND OBJECTIVES

The aim of this article is to develop a methodological approach to differentiating FinTech tools for liquidity management in agribusiness enterprises according to their financial profile, dominant risk and cash flow characteristics, and to identify the corresponding configurations of digital financial solutions using Ukrainian agribusiness companies as examples.

To achieve this aim, the following objectives are set:

1. To systematise the financial profile indicators of the enterprises under study.
2. To identify differences in their cash flow structures.
3. To distinguish typical liquidity management regimes; to establish the correspondence between the financial regime and the priority analytical module.
4. To develop an integrated architecture of "data → forecast → risk → decision → controlled execution."
5. To define criteria for assessing the quality of data, forecasts, models and financial decisions.

METHODS

The empirical basis of the study comprises the official consolidated results of MHP, Astarta and IMC for 2025 (MHP SE, 2026; Astarta Holding PLC, 2026; IMC S.A., 2026). These enterprises were selected on the basis of the public availability of their financial information, the scale of their Ukrainian operations, and the differences in their business models. MHP operates a vertically integrated food production model; Astarta combines crop production, sugar and dairy operations; and IMC focuses primarily on crop production and grain storage. Information published by the companies on digital transformation, AgriChain, and precision agriculture technologies was used to characterise the digital environment (MHP, 2026; Astarta, 2026; IMC, 2026).

The research design is an exploratory comparison of three purposively selected cases, not a representative survey of Ukrainian agribusiness. A common reporting year, 2025, enables a contemporaneous comparison but does not capture variation across production cycles. The cases illustrate the proposed framework; they do not establish the prevalence of the profiles or the effectiveness of the proposed digital tools.

The comparison was based on relative indicators, as MHP and IMC report in US dollars, whereas Astarta reports in euros. Absolute values were not converted using an assumed exchange rate. This approach reduces the influence of scale and reporting currency on the comparison between companies.

The empirical component comprises comparative financial analysis, ratio analysis and interpretation of reported cash flows. Scenario forecasting and risk-based optimisation are specified as proposed components of the management framework, rather than models estimated or tested on the companies' data. The methodological sequence is "financial profile → cash flow forecast → risk assessment → buffer determination → management decision → execution monitoring."

The comparative analysis used dimensionless ratios to reduce distortions arising from currency and scale. The EBITDA margin and net profit margin were calculated as:

$$M_E = \frac{EBITDA}{R} \cdot 100\%, M_N = \frac{NP}{R} \cdot 100\%,$$

where R is revenue, and NP is net profit.

The cash conversion of operating earnings, investment outflow coverage, and relative cash holdings were calculated using the following formulae

$$K_{CF} = \frac{OCF}{EBITDA}, K_I = \frac{OCF}{|ICF|}, K_L = \frac{Cash}{R},$$

where OCF is net operating cash flow; ICF is net cash flow from investing activities; and $Cash$ is cash and cash equivalents at the year-end.

Debt risk is characterised by the net debt-to-EBITDA ratio disclosed by each company. Differences in the treatment of EBITDA adjustments and lease liabilities were taken into account in the interpretation; therefore, the debt ratio is not

regarded as a stand-alone solvency rating. In particular, IMC defines debt as bank borrowings, whereas Astarta's total net debt includes lease liabilities; common leverage thresholds should be used only after these definitions have been reconciled (IMC S.A., 2026; Astarta Holding PLC, 2026).

Profile identification follows two stages. First, annual ratios screen for possible management priorities. Where net investing cash flow is negative, investment outflow coverage below one means that operating cash generation does not cover that net outflow. Cash conversion measures how much reported operating earnings translate into operating cash; cash relative to revenue and net debt relative to EBITDA provide complementary information. These ratios are interpreted together. They do not independently establish the cause of a shortfall or the amount of cash available for discretionary use. Coverage is not interpreted in the same way when net investing cash flow is zero or positive, and EBITDA-based ratios require separate interpretation when EBITDA is zero or negative.

Second, the diagnosis is checked against cash flow details and the payment calendar. An investment-intensive profile requires documented capital expenditure, acquisition or integration payments that create a funding requirement. Working capital pressure requires evidence that inventories, receivables or the timing of supplier payments absorb operating cash; a low cash-conversion ratio alone is insufficient. Potential relative liquidity surplus requires unrestricted cash remaining above scheduled operating, investment and debt payments and the approved seasonal reserve throughout the planning horizon. Undrawn credit supports shortfall protection but is not treated as surplus cash available for investment.

The profiles can overlap. When investment and working capital both create funding needs, the enterprise should combine the corresponding modules and prioritise dates with a projected negative cash balance after available committed financing is considered. If the required supporting information is unavailable, the assignment remains provisional. No universal cut-offs for cash conversion, cash holdings or leverage are estimated from three cases. Operational limits should be set from the enterprise's payment schedule, contractual covenants, historical variability and risk policy; profile assignments should be reviewed when these conditions change.

For practical application, the classification procedure should be implemented as a decision matrix rather than as a rigid ranking of enterprises. The first screening dimension is investment funding pressure, indicated by the relationship between operating cash flow and net investment outflows, supplemented by information on major capital expenditure and acquisition payments. The second dimension is working capital pressure, assessed through changes in inventories and receivables, the timing of supplier payments and the difference between operating earnings and operating cash generation. The third dimension is potential relative liquidity surplus, determined by comparing unrestricted cash and available committed financing with forecast seasonal operating requirements, mandatory investment payments and debt service.

An enterprise is assigned a provisional profile when the relevant financial indicators and cash flow evidence point to the same dominant source of liquidity pressure. Where more than one condition is present, a combined profile is assigned, and the corresponding analytical modules are applied jointly. A profile of potential relative liquidity surplus is confirmed only when forecast cash remains above the required operating and contractual reserve throughout the planning horizon. If the available information is insufficient or the indicators provide conflicting signals, the enterprise remains unclassified until the diagnosis is verified. This procedure separates the initial financial screening from the final management decision and prevents the use of arbitrary numerical thresholds derived from a small number of observations.

The operational layer of the architecture involves creating a consistent set of explanatory variables from bank transactions, enterprise resource planning (ERP) and farm management information systems (FMIS), contract registers, and production and market sources. For enterprise i at time t, the feature vector takes the form:

$$x_{i,t} = \left(CF_{t-1:t-p}, AR_t, AP_t, \mathrm{In}v_t, Debt_t, r_t, P_t, W_t, Y_t, L_t, S_t\right),$$

where $CF_{t\text{-}1:t\text{-}p}$ denotes cash flow lags; AR and AP are receivables and payables; Inv is inventory; $Debt$ denotes debt obligations; r is the cost of financing; P denotes product and input prices; W denotes weather indicators; Y is the yield forecast; L denotes logistics parameters; and S denotes seasonal features.

Since the management decision depends on the lower tail of the distribution, the model is intended to produce not only a point forecast but also a set of conditional quantiles, meaning cash flow levels below which a specified share of possible outcomes is expected to fall:

$$\hat{Q}_{\tau,t+h} = f_{\theta,\tau}(x_t),\ \tau \in \{0{,}05; 0{,}50; 0{,}95\}.$$

DOI: 10.55643/fcaptp.5.70.2026.5327

For tabular data with irregular missing values, gradient boosting with a quantile loss function is a candidate; for multi-horizon forecasting with a large number of time-varying features, the Temporal Fusion Transformer is another candidate (Lim et al., 2021). DeepAR can serve as a baseline probabilistic model for a group of interrelated time series (Salinas et al., 2020). The algorithm should be selected by repeatedly testing forecasts on later observations that were unavailable during model estimation, rather than on the basis of model complexity. A seasonal naïve forecast and a regularised linear model are required as benchmarks (Hyndman & Koehler, 2006; Makridakis et al., 2018).

The additional uncovered funding requirement over horizon h is determined by taking into account the available cash balance C_t, the undrawn and available committed credit facility G_t, and the lower quantile of net cash flow:

$$B_{t,h}=max\{0; -\grave{Q}_{\alpha,t+h} - C_t - G_t\}.$$

For this funding check, the forecast quantile refers to cumulative net cash flow from the forecast date through horizon h. The check should also be applied at intervening payment dates, because a non-negative terminal balance can conceal an earlier funding shortage.

If the cost of financing varies according to maturity and amount, the decision on the credit drawdown, constrained by the approved credit limit, L_t, is expressed by the following simplified constrained funding formulation:

$$\min_{L_t \in \Omega}\left[c_t L_t + \lambda CVaR_a\left(D_{t+1}(L_t)\right)\right],$$

$$D_{t+1}(L_t) = [-(C_t + L_t + CF_{t+1} - P_{t+1})],$$

where c_t is the cost of financing; λ is the risk appetite parameter; P_{t+1} denotes mandatory payments; and Ω is the set of limits and covenants. Here, CVaR (Conditional Value-at-Risk) summarises adverse funding outcomes in the tail of the distribution. The deficit variable is signed: positive values indicate a shortage and negative values a surplus. Cash flow in this financing equation must exclude any mandatory payments deducted separately, to avoid counting them twice.

This formulation separates the forecasting model from policy: a change in risk appetite does not require the forecasting model to be retrained, but changes the recommended buffer.

A combination of rules and Isolation Forest, an algorithm for identifying unusual observations, is proposed to flag payments for review. The rules identify duplicate payment details, limit breaches, unusual timing, and discrepancies with the contract; the model assesses multivariate deviations in amount, counterparty, business unit, frequency, ledger account, and approval route. A map of links between counterparties would supplement the analysis with "supplier → bank account → officer → contract" relationships, enabling the identification of concentrated and cyclical structures that are not visible in a conventional table.

The forecast is explained through SHAP decomposition:

$$f(x) = \phi_0 + \sum_{j=1}^{m} \phi_j,$$

where ϕ_j represents the contribution of a feature to the deviation of the forecast from the baseline (Lundberg et al., 2020).

For the financial manager, what matters is not the feature ranking in itself, but an economically interpretable explanation: an expected deterioration in cash flow is associated with delays in collecting receivables, increasing inventories, or deferred sales. Changes in feature distributions are monitored using the Population Stability Index (PSI), a measure of changes in input distributions; exceeding an internal threshold triggers a review of data sources, backtesting and, where necessary, retraining. SHAP contributions describe the model's associations and do not establish causal effects. The proposed methodology combines an assessment of the enterprises' financial profiles based on actual data with a formalised digital framework for forecasting and liquidity management.

RESULTS

The analysis of the consolidated financial statements of MHP, Astarta and IMC for 2025 revealed substantial differences in their financial profiles. In 2025, MHP generated revenue of USD 3,766 million, an increase of 24% on the previous year,

whereas adjusted EBITDA excluding IFRS 16 amounted to USD 569 million, increasing by only 1% (MHP SE, 2026). The gap between revenue and EBITDA growth reduced the margin to 15.1%. Net profit rose to USD 187 million. Operating cash flow of USD 271 million covered half of the net investment outflow of USD 541 million; investing activities were materially affected by the acquisition of a stake in the Spanish group Uvesa. In a liquidity model, such an event must be coded separately from recurring capital expenditure; otherwise, the algorithm will carry a one-off structural payment into the regular seasonal forecast. The main financial results of the analyzed agro-industrial groups are presented in Table 1.

Table 1. Key financial results of Ukrainian agribusiness groups for 2025. *(Source: compiled from the companies' official consolidated reports (MHP SE, 2026; Astarta Holding PLC, 2026; IMC S.A., 2026).24–26. EBITDA is presented in accordance with each company's methodology)*

Company	Currency, million	Revenue	Change, %	EBITDA	Change, %	Net profit
MHP	USD	3766.0	+24	569.0	+1	187.0
Astarta	EUR	471.9	−23	99.7	−37	19.9
IMC	USD	190.5	−10	95.8	+11	67.5

In 2025, Astarta generated revenue of EUR 471.9 million, EBITDA of EUR 99.7 million, and net profit of EUR 19.9 million (Astarta Holding PLC, 2026). Revenue declined by 23%, EBITDA by 37%, and operating cash flow fell to EUR 36.5 million. The investment outflow of EUR 99.9 million was 2.74 times the operating inflow. With net debt of EUR 226.5 million, the net debt-to-EBITDA ratio was 2.3. The combination of a high EBITDA margin of 21.1% and moderate cash conversion of 36.6% means that the model must monitor working capital separately from accounting earnings, particularly inventories, receivables and the schedule of investment payments.

IMC generated revenue of USD 190.5 million, normalised EBITDA of USD 95.8 million and net profit of USD 67.5 million (IMC S.A., 2026). While revenue declined by 10%, EBITDA increased by 11% and net profit by 24%. Operating cash flow of USD 72.2 million was 6.54 times the investment outflow; the cash balance of USD 45.5 million exceeded bank borrowings of USD 17.9 million, corresponding to net cash relative to bank borrowings (excluding lease liabilities) and a net borrowings-to-EBITDA ratio of $-0{,}3$. IMC's high margins partly reflect the sector-specific accounting treatment of agricultural produce and biological assets under IAS 41, making a direct ranking of the companies by EBITDA margin methodologically inappropriate. For IMC, the priority is not only to prevent shortfalls, but also to assess and manage potential surplus liquidity, cash placement tenors, the foreign currency position, and financing for the forthcoming sowing season.

To provide a more detailed characterisation of the financial profiles, indicators of EBITDA cash conversion, coverage of investment outflows by operating cash flow, relative cash holdings and leverage were used. This set of indicators makes it possible to move beyond assessing operating performance alone to identify the nature of the financial risk that must be addressed in the digital liquidity management system. The calculated cash flow indicators and the corresponding ratios are presented in Table 2.

Table 2. Cash flows and comparative ratios for 2025. Note: OCF is net operating cash flow; ICF is net cash flow from investing activities. Debt ratios are presented in accordance with the companies' methodologies; for MHP, the measure is net debt / LTM adjusted EBITDA net of IFRS 16. IMC reports net bank borrowings / EBITDA, excluding lease liabilities; Astarta's net debt includes leases. These disclosed ratios are not directly equivalent and require harmonisation before applying common leverage limits. IMC's cash conversion is 75.4% from USD 72.161 million / USD 95.761 million; investment coverage is 6.54 from USD 72.161 million / USD 11.039 million. Ratios are calculated before rounding the displayed amounts (IMC S.A., 2026, pp. 11–16).

Company	OCF, million	ICF, million	Cash, million	K_{CF}, %	K_I, times	K_L, %	Reported leverage ratio, times
MHP, USD	271.0	−541.0	415.0	47.6	0.50	11.0	2.7
Astarta, EUR	36.5	−99.9	40.3	36.6	0.37	8.5	2.3
IMC, USD	72.2	−11.0	45.5	75.4	6.54	23.9	−0.3

A comparison of the indicators demonstrates fundamental differences between the financial regimes. MHP's operating cash flow amounted to 47.6% of EBITDA, while its coverage of investment outflows was only 0.50 times, with net debt at 2.7 times EBITDA. This combination characterises an investment-intensive financial profile in which liquidity risk is primarily associated with the synchronisation of operating inflows, investment payments, integration costs and debt financing. Accordingly, the digital solution should focus not only on forecasting current cash flow, but also on scenario modelling of large payments and assessing the adequacy of the financial buffer. The comparative structure of the key financial ratios of the companies under study is presented in Figure 1.

DOI: 10.55643/fcaptp.5.70.2026.5327

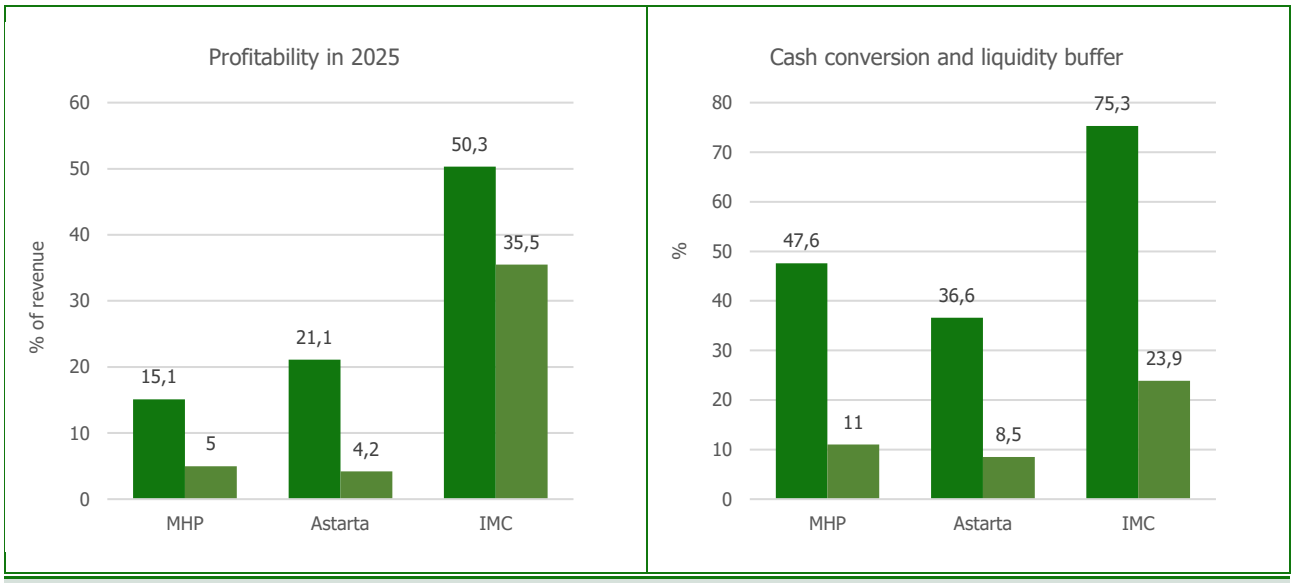


Figure 1. Comparative financial ratios of MHP, Astarta and IMC for 2025. *(Source: calculated from the companies' consolidated financial statements (MHP SE, 2026; Astarta Holding PLC, 2026; IMC S.A., 2026). IMC's cash conversion is 75.4%, and its net profit margin is 35.4%, calculated using unrounded source amounts.*

Astarta has the lowest EBITDA cash conversion among the companies studied, at 36.6%, the lowest investment outflow coverage, at 0.37 times, and cash reserves equivalent to 8.5% of annual revenue. The annual report also records working capital absorption of EUR 67.4 million, reducing operating cash flow from approximately EUR 103.8 million before working capital changes to EUR 36.5 million (Astarta Holding PLC, 2026, p. 14). This directly supports the working-capital-pressure diagnosis, which coexists with investment funding needs; the low cash-conversion ratio alone would not establish its cause. Accordingly, a proposed priority, alongside investment scheduling, is multi-horizon working capital forecasting, early detection of potential cash shortfalls, and dynamic buffer formation.

IMC has a different financial profile: operating cash flow reached 75.4% of EBITDA and was 6.54 times the investment outflow, while cash and cash equivalents represented 23.9% of annual revenue. The company-reported net borrowings-to-EBITDA ratio (−0.3) indicates net cash relative to bank borrowings, excluding lease liabilities. IMC therefore illustrates potential relative liquidity surplus. Its year-end ratios justify examining the allocation of cash, but a freely investable surplus can be confirmed only after seasonal payments, investment commitments, debt service and restricted cash have been assessed.

Based on the aggregate of the indicators presented, three illustrative, potentially overlapping liquidity management profiles were proposed. MHP has substantial absolute cash reserves, but a high investment burden and exposure to the effects of corporate integration; this calls for a scenario model that distinguishes between operating, investment and M&A cash flows. Astarta combines adequate operating profitability with the lowest cash conversion and investment outflow coverage; working capital monitoring and investment scheduling are therefore proposed priorities, subject to confirmation of the underlying cash requirements. IMC has net cash relative to bank borrowings (excluding lease liabilities) and the highest cash-to-revenue ratio among the cases; its model should assess whether cash remains available after seasonal needs and other commitments are covered. Thus, the same algorithm and a single risk threshold cannot be transferred mechanically between enterprises.

The practical application of the classification procedure requires distinguishing the indicator that signals a potential problem from the evidence that establishes its underlying cause. For MHP, investment outflow coverage of 0.50 indicates that operating cash flow did not fully cover net investment outflows in 2025. This result supports the need for investment scenario analysis, but the selection of financing measures must also account for the composition and timing of investment payments. For Astarta, cash conversion of 36.6% and investment outflow coverage of 0.37 indicate substantial pressure on internally generated funding. The reported working capital absorption provides additional evidence for prioritising receivables, inventory and payment schedule analysis. For IMC, cash holdings equivalent to 23.9% of annual revenue and investment outflow coverage of 6.54 indicate a comparatively stronger year-end liquidity position. These indicators justify examining potential surplus cash, but do not independently establish the amount available for discretionary investment.

The comparison therefore illustrates a diagnostic principle: the financial ratio determines which issue requires further examination, while cash flow composition, contractual obligations and the forecast payment calendar determine the appropriate management response. The resulting classification is a decision-support instrument, not a stand-alone solvency rating or an automatic authorisation to execute financial transactions.

At MHP, digital transformation is pursued as a corporate initiative linked to its IT ecosystem and the scaling of digital solutions (MHP, 2026). Its 2025 financial profile indicates a need to consolidate data across geographical and product segments, separately tag integration payments, and monitor covenants under different scenarios. The treasury function's immediate priority is to align payment registers, bank balances, revenue forecasts and the investment budget within a common time frame.

Through its own IT company, AgriChain, Astarta is developing an integrated agricultural production management system covering twelve functional areas. The company reports using computer vision, neural networks, drones and satellite data to monitor crops, forecast yields and identify risks; AgriChain products are also used on more than 350,000 hectares of third-party farmland (Astarta Holding PLC, 2026; Astarta, 2026). This structure enables financial forecasts to be linked to fieldwork plans, material requirements, expected harvests, inventories and logistics.

IMC uses GPS monitoring, more than one hundred automatic steering systems, JD Operations Center, CropWise, Wialon, satellite monitoring, UAVs, yield sensors, weather stations and the PreAgri geoportal; the company also employs variable-rate seeding and input application (IMC S.A., 2026; IMC, 2026). Potential managerial uses of these technologies include more precise planning of fuel, seed, fertiliser and labour requirements, as well as the timing of field operations. Linking telematics to ERP enables payments to be forecast on the basis of economic drivers, rather than simply carrying forward the previous year's amount.

The case comparison illustrates a proposed rule for differentiating financial decisions: diagnostic evidence guides the selection of the management priority, analytical module, forecasting horizon, and approval procedure (Table 3). These configurations are conditional recommendations, not empirically validated prescriptions for the three companies.

Table 3. Proposed configurations of FinTech tools according to the diagnostic financial profile.

Financial profile	Dominant risk	Analytical module	Forecasting horizon	Financial decision
Investment-intensive	Liquidity shortfall due to substantial capital expenditure and integration payments	Scenario-based cash flow forecasting, CVaR analysis	3–6 months	Establishing a liquidity buffer, setting a credit limit, scheduling capital expenditure and major payments
Working capital pressure	Mismatch between the timing of receipts and payments	Quantile cash flow forecasting, early warning	1–13 weeks	Dynamic liquidity buffer, management of receivables and payables
Potential relative liquidity surplus	Suboptimal retention of available cash	Seasonal payment forecasting, buffer optimisation	3–12 months	Reallocation or investment of available cash while maintaining a seasonal buffer

The profile assignment uses the screening and confirmation procedure described in Methods. Profiles may overlap. The forecasting horizons are indicative planning windows, not estimates derived from the three cases; they should be aligned with production cycles, contractual payment dates and financing maturity. Every configuration retains human responsibility for setting risk limits and approving exceptional payments.

The proposed diagnostic mapping is the study's central methodological contribution. It formalises the sequence through which the findings of financial diagnostics are translated into a specific configuration of a digital financial solution. For an investment-intensive profile, the key priorities are assessing scenario-based shortfalls and the cost of obtaining finance; for an enterprise facing working capital pressure, the timeliness of forecasting and early warning; and for an enterprise with a relative liquidity surplus, determining the economically justified amount of funds to be retained in highly liquid form. It combines established tools into a conditional selection procedure; its operational and economic benefits require subsequent testing.

A comparison of the financial profiles with the digital systems already in place at the companies studied illustrates the data sources that could support this differentiation, without demonstrating its effectiveness. MHP is developing a corporate digital environment linked to production and financial processes; Astarta uses AgriChain, satellite data, drones, computer

DOI: 10.55643/fcaptp.5.70.2026.5327

vision and yield forecasting; IMC uses GPS, automatic steering systems, CropWise, Wialon, PreAgri and yield sensors (Table 4).

Table 4. Alignment of digital data sources with liquidity management tasks. *(Source: systematised from official company materials (IMC S.A., 2026; MHP, 2026; Astarta, 2026; IMC, 2026).*

Company	Publicly disclosed digital systems	Financial signals	Priority AI module
MHP	Corporate digital transformation; consolidated production and financial systems	Segment revenue, CAPEX, integration payments, debt and covenants	Scenario-based cash flow forecast and CVaR-based financing limit
Astarta	AgriChain; satellite data; drones; computer vision; yield forecasting	Work plan, resource requirements, inventories, harvest, logistics schedule	Multi-horizon working capital forecasting and early warning
IMC	Automatic steering; GPS; CropWise; Wialon; PreAgri; yield sensors	Hectares covered by field operations, fuel, seeding rates, machinery productivity, warehouse stock levels	Driver-based payment forecasting and assessment of potential surplus cash

The identified relationships underpin an integrated FinTech architecture in which digital tools do not operate in isolation (Figure 2). The first layer collects data from ERP/FMIS, banking application programming interfaces (APIs), which provide authorised data exchange, contract registers, production systems, price and weather data sources, machine monitoring and connected sensors. The second layer performs data cleansing, reconciliation and temporal synchronisation. The third layer forecasts cash flows, estimates the probability of a shortfall, detects anomalous transactions and generates explanations. The fourth layer translates analytical findings into decisions on liquidity buffers, credit limits, payment sequencing, foreign exchange positions and insurance coverage. The fifth layer ensures the controlled execution of transactions after compliance with established rules has been checked and, for specified categories of transactions, human approval has been obtained.

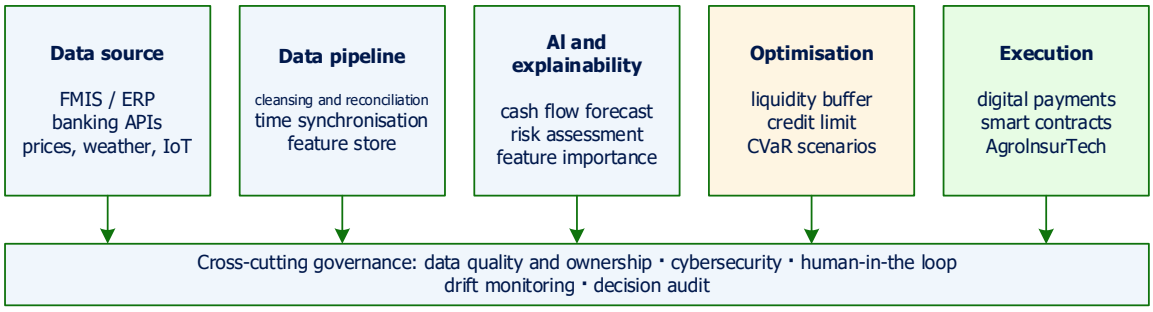


Figure 2. Integrated FinTech architecture for financial resource management.

Model governance is a cross-cutting element. The versions of the data, features, algorithm, forecast, explanation, recommendation, and final decision must be recorded in a single log. Low-risk transactions may be executed automatically within approved limits. Payments to a new counterparty, changes to bank details, budget overruns, a negative liquidity forecast or conflicting model outputs must trigger referral for manual approval. In this system, human review and approval is not merely a stated principle but a formalised workflow with a designated decision owner and response deadline. The logic of transitioning from an analytical result to a specific managerial action and subsequent execution monitoring is presented in Figure 3.

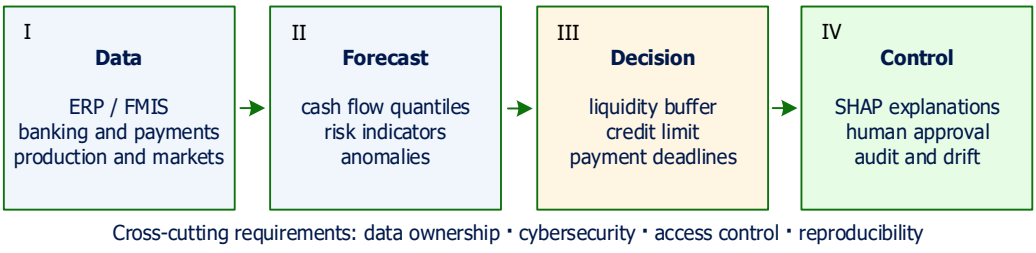


Figure 3. AI-based financial decision-making framework.

Open banking provides the technical capability to retrieve balances and transaction histories and to initiate payments with the user's consent (National Bank of Ukraine, 2026). It should be used as a controlled channel for exchanging banking information rather than as a repository for model logic. Decisions are computed within the corporate environment; the banking API returns the current balance, payment status, and confirmation of execution. This separation of functions reduces dependence on a single provider and facilitates auditing.

Generative language models are suitable for extracting details from contracts, classifying payment purposes, matching invoices against contractual terms and producing textual explanations for financial managers. They should not independently determine loan amounts or authorise payments. Numerical decisions are generated by a verified forecasting and optimisation model, while the language model processes documents within a defined field schema, with mandatory references to source passages and human verification.

The proposed forecasting module should estimate a range of possible cash flows as well as a central forecast. Candidate methods are described in Methods; their selection depends on data availability and comparison with simpler benchmarks. A combination of rules, Isolation Forest, and graph analysis is envisaged for monitoring atypical payments, while explanations should show which inputs influenced a recommendation and how changing relevant assumptions would alter it. CVaR optimisation is proposed for determining the size of the liquidity buffer and credit limit. However, within this article, these algorithms are considered elements of the proposed methodological architecture rather than models empirically tested on enterprises' internal transaction datasets. The management tasks, required data, recommended artificial intelligence methods, expected outcomes, and quality control procedures are systematized in Table 5.

Table 5. Artificial intelligence methods within the financial management framework.

Management task	Data	Method	Output	Quality control
Net cash flow forecasting	Transactions, receivables and payables, inventories, prices, weather, production plan	Quantile boosting; Temporal Fusion Transformer; DeepAR	Cash flow quantiles for 1–13 weeks	Quantile error; interval coverage; scaled error; testing on later periods
Liquidity buffer and credit limit	Forecast scenarios, interest rates, covenants, payment schedule	CVaR optimisation	Funding recommendation subject to approved risk limits	Shortfall frequency, financing cost, stress test
Atypical payments	Amount, time, account, counterparty, contract, approvals	rules; Isolation Forest; graph analysis	Risk score and review workflow	Share of valid alerts among reviewed payments; false blocks; review time
Decision explanation	Model features and forecast	SHAP; counterfactual analysis	Risk factors and conditions for changing the decision	Explanation stability, expert validation
Document processing	Contracts, invoices, acceptance certificates, payment descriptions	Text recognition and language models with source retrieval	Extracted details for compliance review	Field accuracy, completeness of source references, human approval

Forecast quality depends not only on the algorithm but also on the provenance of each indicator. A data profile is compiled for key fields, specifying the source system, owner, unit of measurement, update frequency, permissible delay, and correction rule. Bank transactions are reconciled with payment documents and accounting entries; production operations are matched to the field, crop, machinery unit and agronomic operations plan; yield forecasts are linked to the model version and the date of the satellite image. This record of the origin and processing of data makes it possible to distinguish a genuine change in a financial process from a technical integration error.

The overall suitability of a dataset for forecasting should be monitored using a weighted index:

$$DQ_t = \sum_{k=1}^{n} w_k \, q_{k,t}, \sum_{k=1}^{n} w_k = 1,$$

where $q_{k,t}$ is a normalised score for completeness, timeliness, consistency, uniqueness or reliability; w_k is the criterion weight.

The value of DQ_t must not conceal a critical defect: a missing bank balance or a change in a counterparty's details prevents an automated recommendation, irrespective of a high average score. A minimum set of mandatory features and a simplified operating mode for use when data are incomplete are defined for each model.

Access control is based on the principles of least privilege and segregation of duties. Model developers are not authorised to change payment limits; treasury users cannot modify the forecast log; integration administrators cannot approve new

DOI: 10.55643/fcaptp.5.70.2026.5327

counterparties. Banking API keys are held in a dedicated secure store, have limited validity periods, and carry separate permissions for reading data and initiating payments. Changes to bank details, risk policy, model version, or approval workflow require enhanced verification and generate a protected audit record.

The cyber resilience of financial AI encompasses confidentiality, integrity, availability and recovery. The most serious threats include not only data theft but also undetected distortion of features that alters the forecast liquidity buffer or payment priority. Checks that transferred data have not changed, cross-checks between independent sources, detection of abrupt changes in master data, network segmentation and reconfirmation of critical events are used to mitigate this risk. The business continuity plan must provide for a local copy of the payment schedule, up-to-date bank contact details, a manual approval procedure and a defined maximum recovery time.

Model risk is assessed in terms of the impact of the decision, the degree of autonomy and the reversibility of its consequences. An informational forecast without automated execution falls into a lower risk class; a credit limit recommendation into a higher risk class; and a payment or financing change without prior approval into a critical risk class. The higher the risk class, the more stringent the requirements for independent validation, backtesting frequency, explanation stability and emergency shutdown procedures. Separate stress tests cover loss of the banking channel, logistics disruption, a surge in input prices, delayed payment by a major debtor and a simultaneous decline in forecast revenue.

The use of an external language model requires commercially sensitive data to be isolated. Full bank details, personal data, access keys and unnecessary contractual terms are excluded from the prompt. The model output is validated against a predefined field structure, and each extracted field includes a reference to the relevant passage in the corporate document. Generative AI thus serves as an intelligent interface to the text, while the approved document, the ERP system and bank confirmation remain the sources of truth.

Production deployment should proceed in stages. The first stage establishes a register of data sources and owners and harmonises master data for business units, fields, crops, counterparties, contracts and cash flow categories. Quality is measured by the proportion of transactions with an identified counterparty, contract and timestamp, as well as the time required to reconcile bank records with the ERP system. Modelling begins once the data framework has stabilised.

The second stage involves trial forecasting with no effect on payments. Each week, the model produces quantiles, explanations and a shortfall signal; the treasury function continues its usual process, while forecasts are accumulated for testing against subsequently observed outcomes. A seasonal naïve model, regularised regression and the main algorithm are compared. Acceptance depends not only on lower error but also on calibration: actual cash flow should fall within the 90% interval in approximately nine cases out of ten. An interval that is systematically too wide creates unnecessary liquidity buffer costs, while one that is too narrow conceals the risk of a shortfall.

The third stage provides decision support. The system proposes a liquidity buffer, a credit drawdown amount, payment dates, and a list of factors, but the financial manager approves the decision. An override is recorded with a reason code: a known event, incomplete data, a contract change, an anticipated delay, or an adjustment to risk appetite. These records are used to improve features but should not automatically be treated as evidence of human error.

The fourth stage involves restricted execution. Recurring payments are automated where the amount is low, the contract is verified, the bank details are unchanged, and the forecast buffer is sufficient. Limits are set separately for each business unit, expense type, counterparty and time zone. All other transactions remain subject to dual approval by authorised staff. Smart contracts and parametric insurance are introduced once the event data sources and dispute procedure have been validated. The system of indicators for assessing the operational performance of the digital financial framework, including data quality, forecasting, liquidity, payments, and model management indicators, is presented in Table 6.

Table 6. Operational performance indicator framework.

Area	Key indicator	Intended interpretation	Management response
Data	Completeness of key fields; reconciliation time; proportion of duplicates	Suitability of data for daily forecasting	Blocking an unreliable source; assigning responsibility for correction
Forecast	Scaled forecast error; quantile error; interval coverage; bias	Accuracy and calibration by forecast horizon	Retraining, changing the feature set or reverting to the baseline model
Liquidity	Frequency and severity of shortfalls; liquidity buffer cost	Balance between resilience and financing cost	Adjusting λ, the quantile, or the credit limit
Payments	Share of valid alerts among reviewed payments; false blocks; approval time	Cost-effectiveness of anti-fraud controls	Changing the threshold, rules, or review route
Governance	Changes in input distributions; manual overrides; log completeness	Model stability and accountability	Review of changes in input data, policy review, temporary manual control

For MHP, the initial benefit is expected to come from distinguishing between recurring and structural cash flow and applying scenario-based controls to debt levels. For Astarta, it is expected to come from linking AgriChain to working capital forecasts and the investment schedule. For IMC, it is expected to come from combining telematics with the field operations budget and assessing and managing any cash remaining after seasonal commitments. This differentiation follows from actual financial profiles rather than a universal digitalisation template. The comparative analysis not only characterises the financial position of the three agribusiness groups but also provides an illustrative basis for proposing differentiated digital financial solutions. MHP, Astarta and IMC operate under different liquidity management conditions, so identical forecasting, liquidity buffer and automation parameters cannot be regarded as universally applicable.

DISCUSSION

The case comparison illustrates that an enterprise's profitability cannot be regarded as a sufficient indicator of its ability to maintain adequate liquidity. Astarta reported a lower EBITDA margin than IMC for 2025; however, its lower EBITDA cash conversion and insufficient coverage of investment outflows by operating cash flow are fundamentally more significant for cash flow management. IMC, by contrast, combined high cash conversion with net cash relative to bank borrowings, excluding lease liabilities, although substantial cash reserves do not eliminate the need to account for agricultural production seasonality and future production payments. Despite holding substantial cash reserves in absolute terms, MHP is characterised by a significant investment burden and higher debt levels. Consequently, a digital system focused solely on forecasting profit or aggregate annual financial indicators does not provide an adequate basis for operational liquidity management.

This finding is consistent with FinTech research that treats digital financial technologies as an ecosystem of interconnected technological, financial and institutional components rather than a collection of individual software products (Gomber et al., 2017; Lee & Shin, 2018; Ozili, 2018). For agribusiness enterprises, these interconnections are particularly significant because of production seasonality and the dependence of cash flows on yields, prices, logistics, exchange rate fluctuations, and settlement dates. Accordingly, the digital liquidity management framework must account not only for financial transactions but also for the production factors that shape future receipts and payments. The ability to combine these datasets provides the basis for moving from reactive cash balance monitoring to predictive liquidity management.

The differences identified between MHP, Astarta and IMC illustrate the rationale for refining the logic underpinning the FinTech architecture. A universal configuration of digital tools fails to account for the fact that the same level of liquidity risk may arise from different sources. For MHP, a potential cash shortfall is primarily associated with the scale of investment and integration cash flows; for Astarta, potentially with both working capital absorption and investment funding; and for IMC, with assessing whether year-end cash exceeds forward seasonal requirements. These interpretations require confirmation using the diagnostic procedure in Methods. Digital diagnostics should therefore not only signal the presence of risk but also identify its source and the appropriate financial response mechanism.

The differentiation proposed in this study develops this logic through the sequential relationship "financial profile → dominant risk → digital analytical module → financial decision". Under an investment-intensive profile, priority shifts to scenario-based cash flow forecasting, tail risk assessment, and evaluation of liquidity buffer adequacy. Under working capital pressure, greater emphasis is placed on short- and medium-term quantile forecasting, early warning of cash shortfalls and the management of receivables and payables. Under relative liquidity surplus, the task changes: the digital system must determine the funds required to cover seasonal needs and identify opportunities to deploy surplus cash more efficiently.

Framed in this way, the proposed methodological approach extends the reviewed approaches by specifying a conditional rule for configuring treasury tools in agribusiness. Its distinctive feature is the alignment of the technological solution with the enterprise's specific financial regime. Financial diagnostics identify the dominant risk; the risk determines the priority analytical module; forecasting results determine the liquidity buffer and credit limit parameters; and the established constraints determine the permissible level of automation for the financial transaction. The resulting FinTech architecture is differentiated in both technological and economic terms.

The contribution of the proposed approach should be interpreted at the level of methodological integration and decision differentiation. Its novelty does not consist in the individual use of financial ratios, probabilistic forecasting, risk assessment, or payment anomaly detection, since these methods have established applications in financial management and data analytics. The contribution is the specification of their conditional relationship within a single liquidity management procedure for agribusiness enterprises. In this procedure, the initial financial profile determines the diagnostic priority; the confirmed source of liquidity pressure determines the analytical module; forecast cash flows and contractual constraints inform the required liquidity buffer and financing decision; and the risk level determines the degree of human approval

DOI: 10.55643/fcaptp.5.70.2026.5327

and permissible automation. This structure makes the proposed framework more operationally specific than a general recommendation to digitalise treasury functions.

The empirical cases demonstrate the interpretive value of this procedure by showing that similar liquidity management objectives may require different analytical priorities. However, the study does not establish that the proposed architecture outperforms existing treasury practices or produces measurable financial savings. Such conclusions would require longitudinal data, implementation of the proposed modules, and comparison with baseline management procedures. The present findings therefore provide a methodological basis for subsequent testing rather than a claim of experimentally validated effectiveness.

Comparison with existing research on agricultural sector digitalisation also demonstrates the value of integrating financial and production data. The disclosed digital systems of MHP, Astarta and IMC already cover various aspects of production planning, precision agriculture, resource monitoring and operations. However, the mere presence of digital production systems does not mean that they are automatically used in financial forecasting. The proposed architecture translates production signals into financial signals: expected yields, the volume of field operations, resource requirements, logistics schedules, and changes in production load should become input features for forecasting future receipts and payments.

The economic substance of the proposed architecture is also reflected in the changing role of artificial intelligence. An algorithm should not independently determine an enterprise's financial policy. Its function is to identify patterns in data streams, forecast possible scenarios, detect deviations early, and generate an explainable recommendation. The final financial decision must be made within defined limits, risk policies and control procedures. For this reason, forecasting, CVaR optimisation, anomaly detection and SHAP explanations should be considered interconnected elements of a single framework rather than a set of independent technological solutions.

The proposed logic establishes a closed loop: "financial profile → forecast → risk → decision → controlled execution". Its practical value lies in linking the output of the analytical module directly to a specific financial action: establishing or adjusting a liquidity buffer, revising a credit limit, rescheduling a payment, adjusting the investment calendar or optimising surplus cash balances. At the same time, controlled automation requires the retention of information on the data source, the model used, the forecast generated, the explanation of the recommendation and the actual decision. This requirement is fundamental to financial transactions, since an input data error or model instability must not automatically result in an uncontrolled payment action.

Nevertheless, the findings must be considered in the light of the study's limitations. The comparison uses one reporting year and three purposively selected large groups, and is not statistically representative of Ukrainian agricultural enterprises, particularly smaller farms. It cannot capture changes across production cycles or establish sector-wide effects. The companies differ in business structures, reporting currencies, and approaches to calculating adjusted EBITDA. The use of relative indicators reduces the effects of scale and currency but does not eliminate all differences between the enterprises. Moreover, annual reports enable the strategic financial profile to be identified but do not replace the daily or weekly transaction data required for comprehensive backtesting of forecasting models.

Accordingly, the quantile forecasting, Isolation Forest, graph analysis, SHAP, and CVaR proposed in this article should be regarded as methodological tools within the proposed architecture, rather than models whose effectiveness has already been statistically validated using the enterprises' internal datasets. The next stage of research should test the proposed configuration using daily or weekly observations spanning several production cycles and a broader, more diverse set of enterprises to determine forecast accuracy, false signal frequency, liquidity buffer costs, and the economic consequences of financial decisions. This validation will make it possible to assess both the technical performance of individual algorithms and the economic impact of their integration into the liquidity management system.

Validation should compare the proposed configuration with existing payment planning and simpler forecasting methods on observations outside the model-development period. It should assess whether profile assignments remain stable, whether funding shortages and financing costs decrease, and whether false payment alerts are acceptable. No such comparative effectiveness test has been performed in this study; the reported ratios demonstrate differences between the cases, not improvements caused by the architecture.

CONCLUSIONS

This study proposes a methodological approach to differentiating digital financial solutions for liquidity management in agribusiness enterprises according to their financial profiles, dominant risks, and cash flow characteristics. It formalises the proposed sequential relationship "financial profile → dominant risk → digital analytical module → financial decision",

which determines the functional configuration of the intelligent FinTech architecture. Its foundation is a closed loop combining production and financial data, cash flow forecasting, risk assessment, the generation of a financial recommendation, and the controlled execution of a transaction.

The comparative analysis of MHP, Astarta and IMC for 2025 illustrated three potentially overlapping management profiles for liquidity management. EBITDA cash conversion was 47.6, 36.6 and 75.4%, respectively; relative cash holdings were 11.0, 8.5 and 23.9%; and coverage of investment outflows by operating cash flow was 0.50, 0.37 and 6.54 times. Subject to confirmation of payment schedules and the sources of cash absorption, these profiles suggest differentiated digital financial solutions: for MHP, the priorities are scenario-based management of investment cash flows and debt levels; for Astarta, forecasting working capital, cash shortfalls and a dynamic liquidity buffer; and for IMC, forecasting seasonal payments and assessing potential cash available after seasonal and contractual commitments.

The methodological framework developed provides for the use of quantile forecasting to estimate future cash flows, anomaly detection algorithms and graph analysis to monitor payments, SHAP to explain model outputs, and CVaR to account for liquidity shortfall risk when determining the liquidity buffer and credit limit. Within this article, these algorithms are considered components of the proposed methodological architecture, rather than models whose empirical effectiveness has already been validated using internal enterprise transaction data. Generative language models should be used to produce structured data fields and explanations, subject to mandatory human review of the output. The automated execution of financial transactions must remain within formalised limits, comply with established rules and use reliable data sources.

The practical application of the proposed approach involves a phased progression from data inventory and normalisation to trial forecasting without execution of payments, financial decision support and, once model stability has been confirmed, limited automation. The performance assessment of this framework should cover not only forecast accuracy but also the frequency and magnitude of liquidity shortfalls, the cost of holding the liquidity buffer, the proportion of incorrectly blocked payments, the stability of model features and the completeness of the audit trail. Accordingly, the practical value of the proposed architecture lies in its ability to link digital analytics to specific parameters of an enterprise's financial decisions, rather than to automation in the abstract.

The proposed methodological framework therefore requires further empirical validation through backtesting on internal enterprise time series to determine forecasting accuracy, the frequency of false signals, the cost of maintaining liquidity buffers, and the economic consequences of the financial decisions taken. Until broader, multi-year validation is available, the proposed profiles should be used as diagnostic hypotheses rather than universal categories or evidence of improved performance.

ADDITIONAL INFORMATION

AUTHOR CONTRIBUTIONS

Conceptualization: *Svitlana Kachula, Oleh Onopriienko*

Data curation: *Oleh Onopriienko, Valentyn Bakumov, Oksana Pavlenko*

Formal Analysis: *Svitlana Kachula, Oleh Onopriienko, Svitlana Khalatur*

Methodology: *Svitlana Kachula, Oleh Onopriienko, Svitlana Khalatur*

Software: *Oleh Onopriienko, Valentyn Bakumov*

Resources: *Svitlana Khalatur, Oksana Pavlenko, Ilona Solodovnykova, Valentyn Bakumov*

Supervision: *Svitlana Kachula, Svitlana Khalatur*

Validation: *Svitlana Khalatur, Valentyn Bakumov, Oksana Pavlenko*

Investigation: *Svitlana Kachula, Oleh Onopriienko, Svitlana Khalatur, Valentyn Bakumov, Oksana Pavlenko, Ilona Solodovnykova*

Visualization: *Oksana Pavlenko, Ilona Solodovnykova*

Project administration: *Svitlana Kachula, Svitlana Khalatur, Oleh Onopriienko*

Funding acquisition: *Svitlana Khalatur, Valentyn Bakumov, Oksana Pavlenko, Ilona Solodovnykova*

Writing – review & editing: *Svitlana Kachula, Oleh Onopriienko*

Writing – original draft: *Svitlana Kachula, Oleh Onopriienko, Svitlana Khalatur, Valentyn Bakumov, Oksana Pavlenko, Ilona Solodovnykova*

DOI: 10.55643/fcaptp.5.70.2026.5327

FUNDING

The Authors received no funding for this research.

CONFLICT OF INTEREST

The Authors declare that there is no conflict of interest.

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Качула С., Онопрієнко О., Халатур С., Павленко О., Бакумов В., Солодовникова І.

ІНТЕЛЕКТУАЛЬНА ФІНТЕХ-АРХІТЕКТУРА ДЛЯ УПРАВЛІННЯ ЛІКВІДНІСТЮ В АГРОБІЗНЕС-ПІДПРИЄМСТВАХ: МЕТОДОЛОГІЧНИЙ ПІДХІД ДО ДИФЕРЕНЦІАЦІЇ ФІНАНСОВИХ РІШЕНЬ

У дослідженні запропоновано методичний підхід до диференціації фінтех-рішень для управління ліквідністю в агробізнес-підприємствах за їхнім фінансовим профілем, домінуючим ризиком і характеристиками грошового потоку. Підхід узгоджує фінансову діагностику підприємства з вибором аналітичного модуля, горизонтом прогнозування, параметрами буфера ліквідності й рівнем автоматизації в ухваленні фінансових рішень. Розвідувальне порівняння трьох цільово відібраних підприємств ґрунтується на даних офіційних консолідованих звітів MHP, Astarta й IMC за 2025 рік, доповнених публічно доступною інформацією компаній про цифрові системи та управлінські технології. Для порівняння підприємств використано відносні показники конверсії EBITDA в операційний грошовий потік, покриття інвестиційних відтоків операційним грошовим потоком, відносні грошові резерви та боргове навантаження. Виявлено відмінності у фінансових профілях підприємств: співвідношення операційного грошового потоку до EBITDA становило 47,6% для MHP, 36,6% для Astarta й 75,4% для IMC; грошові кошти та їх еквіваленти становили відповідно 11,0%, 8,5% й 23,9% річного доходу; а покриття інвестиційних відтоків операційним грошовим потоком становило 0,50, 0,37 і 6,54 раза. На прикладі цих підприємств проілюстровано три профілі, які можуть поєднуватися: інтенсивне інвестування, тиск оборотного капіталу та потенційний відносний надлишок ліквідності. Запропонована фінтех-архітектура пов'язує облікові, виробничі та банківські дані з прогнозуванням грошових потоків, перевіркою незвичних платежів і оцінюванням несприятливих сценаріїв фінансування. Послідовність «фінансовий профіль → домінуючий ризик → цифровий аналітичний модуль → фінансове рішення» визначає методичний внесок: правила узгодження фінансової діагностики з вибором інструментів, горизонтом планування та процедурою погодження рішень відповідальною особою. Запропоновано критерії для оцінки ефективності системи, що охоплюють точність і калібрування прогнозів, частоту й величину дефіциту ліквідності, вартість буфера ліквідності, частку неправильно заблокованих платежів, стабільність вхідних ознак моделі та повноту аудиторського сліду. Дані трьох підприємств за один рік не забезпечують репрезентативності для галузі та не доводять ефективності запропонованих інструментів: потрібна подальша перевірка на ширшій вибірці за кілька виробничих циклів.

Ключові слова: фінансові технології, штучний інтелект, агробізнес, ліквідність, грошовий потік, фінтех, відкритий банкінг, пояснюваний штучний інтелект, CVaR, ERP, FMIS

JEL Класифікація: G32, G17, O33, Q12

DOI: 10.55643/fcaptp.5.70.2026.5327