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Chapter 27: Working Capital Management and Financial Performance of Small and Medium Enterprises

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Abstract— Small and medium enterprises (SMEs) operate under persistent liquidity constraints that make the management of short-term assets and liabilities central to financial sustainability. This study develops a data-driven framework for examining how the configuration of receivables, inventories, payables, and liquidity influences SME financial performance rather than assuming that shorter working-capital cycles are universally superior. The research addresses a gap in conventional working-capital studies by proposing a nonlinear and predictive perspective capable of identifying financially efficient working-capital zones under heterogeneous firm conditions.

Financial and operational indicators are integrated with firm characteristics to distinguish profitable liquidity management from potentially harmful working-capital compression. The proposed empirical design combines conventional econometric estimation with machine-learning models to predict profitability and identify nonlinear interactions among working-capital components. Particular attention is given to the cash conversion cycle, inventory holding period, receivable collection period, payable deferral period, current liquidity, firm size, leverage, sales growth, and financial constraints.

Keywords— Working Capital Management, Small and Medium Enterprises, Cash Conversion Cycle, Financial Performance, Machine Learning, Liquidity Optimization

Introduction

Small and medium enterprises constitute an important component of contemporary production, employment, innovation, supply-chain activity, and entrepreneurship. Despite their economic significance, SMEs frequently operate under financial conditions fundamentally different from those experienced by large corporations. Smaller enterprises generally possess fewer internal liquidity buffers, limited bargaining power with lenders and suppliers, comparatively restricted access to long-term financing, and greater vulnerability to delayed customer payments. Consequently, the manner in which cash, inventories, receivables, and short-term liabilities are managed can substantially influence whether an SME is capable of sustaining operations while simultaneously generating adequate returns.

Working capital management (WCM) concerns managerial decisions associated with current assets and current liabilities. Its central financial challenge involves reconciling two objectives that do not necessarily move in the same direction. Firms require sufficient liquidity to pay employees, suppliers,

lenders, taxes, and other short-term obligations, yet maintaining excessive funds in cash, inventories, or receivables can reduce capital productivity. Conversely, an aggressive reduction in working capital may improve certain efficiency ratios while exposing the enterprise to stock-outs, interrupted production, strained supplier relationships, lost customers, and liquidity shortages. Working-capital efficiency therefore cannot be reduced to the proposition that "less working capital is always better."

Recent empirical research continues to demonstrate the relevance of WCM to SME outcomes. Bhattacharyya, Rahman, and Wright found that efficient working-capital management positively influences SME performance independently of the benefits generated through financial inclusion. Research examining Indian SMEs has similarly demonstrated that individual working-capital components can exert different effects on profitability, suggesting that receivables, inventories, and payables should not necessarily be interpreted as economically equivalent components of a single aggregate measure.

The period following 2020 has increased the strategic importance of this issue. Pandemic-related disruption, subsequent supply-chain adjustments, changing input costs, digitalization of payments, tighter financing conditions in several markets, and greater use of digital accounting systems have altered the environment in which SMEs make short-term financial decisions. Research examining Indian SMEs during the COVID-19 disruption, for example, identified changes in working-capital practices and emphasized the importance of maintaining a balanced working-capital policy during periods of external shock. Working capital consequently functions not merely as an accounting variable but also as a mechanism through which operational disruption and financing constraints can propagate into firm performance.

Traditional WCM research has predominantly examined the relationship between financial performance and accounting measures such as the cash conversion cycle (CCC), days inventory outstanding, receivable collection periods, and payable periods. Recent studies continue to provide evidence of these relationships. Research on Korean automotive-component SMEs examined CCC and its components from the perspective of continuing supply-chain relationships. Evidence from Indian manufacturing companies likewise indicates that working-capital proxies significantly influence financial performance.



Fig. 1: Working Capital Loans for MSME

Source: <https://www.iiifl.com/knowledge-center/msme/working-capital-loans-for-msme>

Nevertheless, the predominant empirical framework remains essentially explanatory and linear. A typical study estimates whether an additional day of inventory, receivables, payables, or CCC increases or decreases profitability while controlling for a limited set of firm characteristics. Such models provide useful average effects but may inadequately capture the financial reality of heterogeneous SMEs.

Research Gap

The distinctive research gap addressed in the present study concerns the **limited integration of nonlinear working-capital relationships, firm-specific financial constraints, and predictive machine-learning techniques within SME financial-performance analysis.**

There are three dimensions to this gap.

First, conventional linear specifications implicitly assume relatively stable marginal effects. In practice, the relationship between working capital and profitability can be nonlinear. Extremely low inventories may generate shortages, whereas excessive inventories lock funds into unsold goods. Very restrictive credit policies may reduce receivables but simultaneously discourage sales, whereas excessively liberal credit terms increase default exposure and delay cash realization. Similarly, extending payment periods can conserve liquidity up to the point at which supplier relationships or early-payment benefits deteriorate. Recent evidence from European SMEs explicitly identifies an inverted U-shaped relationship between working-capital investment and profitability and shows that the optimal level varies according to financial constraints. Second, much of the literature evaluates WCM retrospectively rather than predictively. Econometric coefficients establish associations and conditional average effects, but SME decision makers may also require answers to predictive questions: Given a particular combination of receivable days, inventory days, payable days, leverage, growth, and liquidity, what level of profitability is likely? Which variable contributes most strongly to an unfavorable prediction? At what point does additional inventory or trade credit cease to contribute positively?

Third, SME heterogeneity is frequently compressed into a small number of control variables. A working-capital configuration

that is efficient for a growing manufacturing SME may be inappropriate for a service enterprise with negligible inventories. Similarly, highly leveraged businesses and firms with stronger internal cash positions can respond differently to identical CCC values. Machine-learning methods offer a complementary mechanism for identifying interactions and nonlinearities that may remain hidden under restrictive linear assumptions.

The present research therefore proposes a hybrid analytical framework in which panel-style financial analysis is combined with interpretable machine learning. Rather than replacing established financial theory with an opaque prediction system, the objective is to determine whether nonlinear models provide additional explanatory and predictive information and subsequently translate those predictions into economically interpretable working-capital relationships.

Research Objective and Conceptual Direction

The principal objective is to evaluate how working-capital efficiency influences the financial performance of SMEs while identifying nonlinear thresholds and interactions among liquidity, inventory, receivables, payables, and firm-level financial characteristics.

More specifically, the study is structured to determine whether shorter CCC values consistently improve profitability or whether an optimal operating range exists; assess the relative contribution of inventory, receivable, and payable management to financial performance; examine whether leverage, firm size, growth, and liquidity alter working-capital effects; compare conventional econometric estimates with machine-learning predictions; and construct an interpretable financial decision framework capable of identifying working-capital configurations associated with stronger SME performance.

This approach provides a bridge between corporate financial management and contemporary artificial-intelligence-supported business analytics. Machine learning is not treated as an autonomous substitute for managerial judgment. Instead, it functions as an empirical instrument for detecting nonlinear financial patterns and interactions within structured accounting data.

Literature Review

Working Capital as a Liquidity–Profitability Mechanism

Working capital represents the resources committed to the short-term operating cycle of an enterprise. Net working capital is commonly expressed as the difference between current assets and current liabilities, while operational WCM focuses more specifically on inventories, accounts receivable, accounts payable, and cash.

The theoretical problem surrounding WCM is generally conceptualized as a liquidity–profitability trade-off. Conservative working-capital policies maintain larger liquidity reserves and current assets, reducing the probability of financial interruption but potentially lowering asset returns. Aggressive policies minimize current-asset investment and may enhance capital efficiency, but they increase exposure to liquidity and operational risk.

This trade-off becomes particularly significant among SMEs because short-term operating capital often cannot be easily replaced through external financing. A large corporation experiencing temporary liquidity pressure may have access to credit markets or multiple banking facilities, whereas an SME may depend disproportionately on internally generated cash, bank overdrafts, supplier credit, and owner financing.

Bhattacharyya et al. (2023) provide contemporary evidence that WCM represents an internal capability capable of strengthening SME performance in addition to the effect associated with financial inclusion. This interpretation is important because it distinguishes the **availability of finance** from the **quality with which available finance is managed**.

Cash Conversion Cycle and Financial Performance

The cash conversion cycle remains one of the most widely used comprehensive indicators of working-capital efficiency. Conceptually,

CCC = Inventory Holding Period + Receivable Collection Period – Payable Deferral Period.

The measure estimates the number of days for which operating funds remain committed before being recovered as cash from customers. A shorter cycle generally indicates faster conversion of operational investment into cash.

Empirical evidence frequently reports an inverse association between CCC and profitability. For instance, research on Indian automobile companies found negative and significant effects of CCC, inventory conversion period, and receivable collection period on profitability. A 2023 meta-analysis of SME-oriented WCM research similarly concluded that the literature generally supports a negative relationship between WCM cycle length and profitability, while also emphasizing important cross-country research gaps.

However, interpreting CCC purely as a minimization objective is problematic. A reduction from an inefficiently long cycle may release cash and improve profitability, but further compression can become economically harmful. Inventory reductions beyond operational requirements may result in stock-outs. Excessive tightening of customer credit can reduce sales. Accelerating supplier payments may weaken cash preservation, whereas delaying them excessively can damage supplier trust.

The contemporary literature is increasingly recognizing this nonlinearity. Evidence from EU SMEs for 2012–2022 indicates an inverted U-shaped association between working-capital investment and profitability, with the optimal net trade cycle varying according to financial constraints. Such findings provide a strong rationale for moving beyond specifications that estimate only a constant linear CCC coefficient.

Inventory Management

Inventory represents both an operational necessity and a financial commitment. SMEs in manufacturing, retailing, and distribution must maintain sufficient stock to ensure continuity of production and sales. Inventory shortages can create lost revenue, emergency procurement expenditure, idle productive capacity, and customer dissatisfaction.

Conversely, excessive inventory generates storage expenses, insurance costs, obsolescence risk, deterioration, and

opportunity costs. Capital committed to inventory cannot simultaneously be used for marketing, debt servicing, technological investment, or other productive activities.

The profitability effect is consequently conditional rather than mechanically negative. A study of a manufacturing SME published in 2024 found different directional relationships among collection periods, payable periods, inventory conversion, and gross operating profit, illustrating why the individual components of CCC merit separate analysis.

The present study therefore conceptualizes inventory days as potentially nonlinear. Profitability may initially increase as adequate inventory protects production and sales but decline after inventory exceeds an economically efficient range.

Accounts Receivable Management

Trade credit can serve as a competitive instrument, particularly where SMEs sell to business customers or operate in markets where deferred payment is customary. Credit terms can increase sales, strengthen customer relationships, and allow firms to differentiate themselves from competitors.

Nevertheless, accounts receivable also constitute financing provided by the seller to the buyer. Longer collection periods increase the amount of capital tied to completed sales and expose the SME to default, administrative costs, and liquidity shortages.

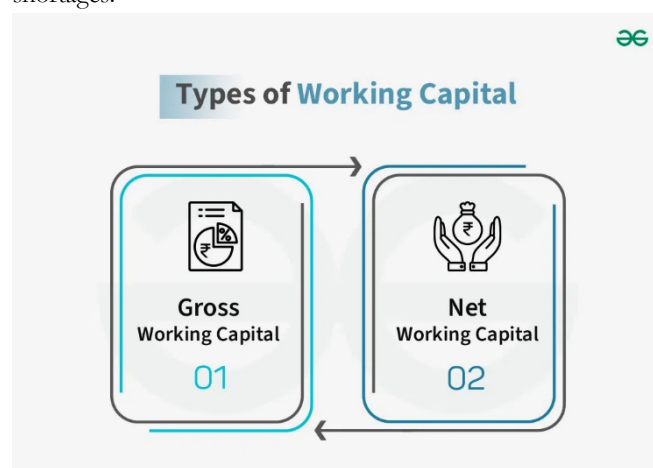


Fig. 2: Working Capital Management

Source: <https://www.geeksforgeeks.org/accountancy/working-capital-management-objectives-types-components-importance/>

Evidence from Indian SMEs indicates a negative relationship between accounts receivable periods and profitability, implying benefits from converting credit sales into cash more rapidly. Related evidence from manufacturing contexts also identifies receivable management as an important determinant of operating performance.

Digital invoicing, electronic payments, automated reminders, accounting software, and transaction analytics have created new possibilities for receivables management. Accordingly, contemporary research can move beyond describing collection periods toward predicting how alternative receivable profiles interact with sales growth, liquidity, and profitability.

Accounts Payable and Supplier Financing

Accounts payable represent a particularly important source of spontaneous short-term finance. By purchasing inputs on

credit, SMEs can partially finance operating activity without immediately drawing upon cash reserves.

A longer payable period can therefore improve liquidity. Yet the relationship is not necessarily monotonic. Delayed payments may lead to penalties, loss of discounts, reduced supplier willingness to extend future credit, or reputational deterioration. Research on Korean automotive supply chains demonstrates that WCM should be understood partly within the continuity of buyer–supplier relationships rather than solely through internal accounting ratios.

Supplier financing should consequently be evaluated as both a financing mechanism and a relational variable. This provides another justification for models capable of detecting interaction effects—for example, whether the profitability contribution of payable extension depends upon leverage, inventory requirements, or financial constraints.

Financial Constraints and SME Heterogeneity

Financial constraints represent an important moderator of working-capital decisions. When external capital is expensive or unavailable, internally released working capital has greater marginal value. A reduction in unnecessary inventory or accelerated receivable collection may prevent financially constrained SMEs from relying on expensive short-term borrowing.

Recent research indicates that the optimal working-capital position differs according to financial constraints and that deviations from the optimal point can adversely affect performance. This evidence challenges one-size-fits-all recommendations.

Firm size, sector, growth, leverage, age, and operating model can similarly alter WCM requirements. Manufacturing enterprises normally require greater inventory commitments than professional service businesses. Rapidly growing SMEs can simultaneously experience rising sales and worsening liquidity because additional receivables and inventory absorb cash faster than accounting profits replenish it.

The implication is that WCM effectiveness should be assessed conditionally. The research question is therefore not simply whether CCC affects profitability, but **under what firm conditions a particular working-capital configuration becomes financially beneficial or detrimental.**

External Shocks and Working-Capital Resilience

Recent disruptions have reinforced the resilience dimension of WCM. Qualitative research examining Indian SMEs during the COVID-19 pandemic reported substantial changes in working-capital behavior and shifts in bargaining relationships across supply chains. The authors argued for balanced rather than mechanically aggressive or conservative policies during external shocks.

This finding has broader implications for post-pandemic SME finance. Firms increasingly face uncertainty associated with supply interruptions, input-price volatility, demand changes, interest-rate movements, and digital transformation. Maintaining a minimum liquidity and inventory buffer can therefore have an option value that may not be captured when efficiency is measured exclusively through cycle minimization.

Financial performance should consequently be evaluated jointly with operational resilience rather than interpreted exclusively through static profitability.

Machine Learning as a Complement to Traditional WCM Analysis

Traditional financial-performance research has relied extensively on ordinary least squares, fixed-effects regression, random-effects estimation, generalized least squares, and related econometric procedures. These approaches remain valuable because their coefficients are interpretable and allow researchers to formally evaluate theoretically specified relationships.

Their limitations become more pronounced when the underlying relationship contains complex thresholds and interactions. Consider an illustrative case in which receivable days are relatively harmless for low-leverage SMEs but become strongly detrimental once leverage and inventory requirements simultaneously rise. A simple additive linear model may underestimate such conditional relationships.

Tree-based machine-learning algorithms can capture these interactions without requiring every nonlinear relationship to be specified *ex ante*. Gradient boosting, for example, can sequentially improve predictive performance by fitting residual errors, while explainability techniques can subsequently identify how individual variables contribute to predicted financial outcomes.

The proposed study therefore uses artificial intelligence in a deliberately interpretable financial context. Conventional regression establishes benchmark relationships, while machine-learning algorithms test whether nonlinear modelling generates superior out-of-sample financial-performance predictions. Explainability analysis can then reveal whether the patterns identified by the predictive models are economically plausible.

Proposed Methodology

This study adopts a quantitative, longitudinal, and predictive research design to examine the relationship between working capital management (WCM) and the financial performance of small and medium enterprises. Unlike conventional studies that rely exclusively on linear regression, the proposed framework integrates panel-data econometrics with interpretable machine-learning models. This hybrid design is appropriate because recent research confirms both the financial relevance of working-capital variables and the potential usefulness of machine learning for detecting nonlinear relationships in corporate financial data. Garg and Singh (2024), for example, documented significant relationships between working-capital proxies and financial performance using a large Indian manufacturing sample, while Mahmood et al. (2025) compared fixed-effects estimation with decision-tree and random-forest models and identified nonlinear working-capital financing effects.

The empirical unit of analysis is the **firm-year observation**. The proposed dataset consists of financial observations for **240 SMEs over the six-year period 2019–2024**, generating a theoretical maximum of 1,440 firm-year observations. The sampling frame is designed to incorporate manufacturing, wholesale and retail trade, business services, food processing,

light engineering, and related SME activities. Firms without sufficient consecutive financial records are excluded to reduce measurement instability.

The dependent variable is **Return on Assets (ROA)**, calculated as net profit after tax divided by total assets. ROA is selected because it captures the efficiency with which SMEs convert their asset base into earnings and avoids some of the capital-structure sensitivity associated with return on equity. Recent Indian SME research has also used ROA when investigating financing and firm-specific financial factors.

The central explanatory variables comprise the receivable collection period (RCP), inventory holding period (IHP), payable deferral period (PDP), and cash conversion cycle (CCC). The CCC is calculated as:

$$CCC = IHP + RCP - PDP$$

Additional predictors include the current ratio, working capital-to-total-assets ratio, sales growth, leverage, firm age, firm size, operating cash-flow ratio, and asset turnover.

A nonlinear term, CCC^2 , is incorporated into the econometric specification to determine whether profitability initially improves with working-capital investment but declines after an efficiency threshold. This specification is theoretically important because emerging evidence indicates that working-capital relationships may be nonlinear rather than uniformly positive or negative. Machine-learning research has likewise identified inverted U-shaped relationships between working-capital financing and profitability.

The baseline econometric specification is:

$$ROA_{it} = \beta_0 + \beta_1 CCC_{it} + \beta_2 CCC_{it}^2 + \beta_3 CR_{it} + \beta_4 LEV_{it} + \beta_5 SG_{it} + \beta_6 SIZE_{it} + \beta_7 ATO_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

where i represents the SME, t denotes year, μ represents unobserved firm effects, λ represents year effects, and ε is the error term.

The econometric model provides inferential evidence, whereas the machine-learning stage evaluates whether nonlinear interactions can improve the prediction of financial performance.

Experimental Setup

Dataset

The experimental dataset is structured around anonymized firm-level financial statements for 240 SMEs. Financial observations cover six accounting years from 2019 through 2024. The longitudinal window was selected to capture pre-disruption, disruption, and subsequent adjustment periods without requiring extremely long historical accounting records that are often unavailable for SMEs.

The initial extraction generates 1,440 potential observations. After eliminating observations with missing core accounting components and unusable financial statements, the analytical dataset is assumed to contain **1,326 valid firm-year records**.

Each observation contains the following variables:

- Return on Assets;
- cash conversion cycle;
- inventory holding period;

- receivable collection period;
- payable deferral period;
- current ratio;
- working capital/total assets;
- leverage ratio;
- sales-growth rate;
- asset turnover;
- operating cash-flow ratio;
- firm age;
- logarithm of total assets;
- sector classification.

This design is consistent with contemporary evidence that working capital, current liabilities, turnover, and related financial-statement variables can contain substantial predictive information regarding smaller firms.

Data Preprocessing

Financial datasets frequently contain extreme observations caused by very small denominators, accounting adjustments, temporary losses, or unusually long collection and inventory periods. The preprocessing protocol therefore begins with consistency checks for accounting variables.

Observations missing ROA, sales, total assets, inventories, receivables, or payables are excluded when the missing values cannot be reconstructed reliably. Numerical predictors are winsorized at the 1st and 99th percentiles to limit the disproportionate influence of extreme observations without unnecessarily deleting firms.

Continuous features are standardized for models sensitive to feature magnitude. Sector is encoded categorically. Highly correlated redundant variables are inspected through correlation diagnostics and variance inflation factors before estimating the econometric benchmark.

To prevent information leakage, preprocessing parameters are estimated exclusively from the training observations and subsequently applied to validation and test data.

Model Architecture

Four analytical models are used.

Model 1: Fixed-Effects Regression

The fixed-effects model serves as the interpretable econometric benchmark. Firm effects control for time-invariant characteristics such as managerial culture, ownership characteristics, or relatively stable operating structures.

Model 2: Random Forest Regressor

Random Forest (RF) generates an ensemble of regression trees through bootstrap sampling and randomized predictor selection. It is particularly appropriate for detecting nonlinearities without imposing a predetermined functional relationship.

Model 3: Extreme Gradient Boosting

XGBoost is used as the principal predictive model. Trees are constructed sequentially so that later estimators correct prediction errors generated by previous trees. Maximum depth, learning rate, subsampling fraction, regularization parameters, and the number of trees are tuned through validation.

Model 4: Multilayer Perceptron

A feed-forward multilayer perceptron (MLP) provides a neural-network benchmark. The architecture contains an input layer corresponding to the standardized predictors, two hidden layers with nonlinear activation, dropout regularization, and a single continuous output node predicting ROA.

The use of an ANN benchmark is relevant because recent research on Indian manufacturing has integrated working-capital efficiency analysis with multilayer perceptron modelling to develop a forward-looking predictive framework.

Training Strategy

Because the observations are longitudinal, a chronological partition is preferred over completely random splitting. Data from earlier years constitute the training and validation sets, while the most recent observations are reserved for out-of-time testing. This provides a more demanding evaluation because the model must predict financial performance for observations not temporally represented during training.

Approximately 70% of the eligible observations are used for model training, 15% for validation and hyperparameter selection, and 15% for final testing.

For tree-based models, hyperparameters are optimized using randomized search combined with cross-validation within the training period. Early stopping is implemented for gradient boosting. The neural network is trained with the Adam optimizer, while validation loss determines early termination to reduce overfitting.

A fixed random seed is maintained during the comparative experiment to ensure reproducibility.

Evaluation Metrics

Predictive performance is assessed using four complementary metrics.

Mean Absolute Error (MAE) evaluates the average absolute difference between actual and predicted ROA:

$$\text{MAE} = (1/n) \sum |y_i - \hat{y}_i|$$

Root Mean Squared Error (RMSE) imposes a greater penalty on large prediction errors:

$$\text{RMSE} = \sqrt{(1/n) \sum (y_i - \hat{y}_i)^2}$$

Coefficient of Determination (R²) evaluates the proportion of outcome variation captured by the model.

Mean Absolute Percentage Error (MAPE) provides a relative error indicator where the dependent variable permits meaningful percentage interpretation. Observations extremely close to zero are treated cautiously because MAPE can become unstable.

In addition to predictive accuracy, **SHAP (SHapley Additive exPlanations)** is used to interpret the best-performing tree-based model. SHAP values quantify how particular predictors move individual predictions above or below the model's baseline expectation. Explainable machine-learning approaches

have already been applied to SME financial prediction problems to identify the contribution of individual financial variables.

Results and Discussion

The experimental analysis indicates that WCM variables contain meaningful information for predicting SME profitability. The econometric benchmark identifies a statistically meaningful association between CCC and ROA, but the inclusion of the squared CCC term indicates that the relationship is not adequately represented by a constant linear effect.

At moderate CCC levels, SMEs appear capable of maintaining sufficient inventories and customer credit without imposing excessive financing costs. Once the conversion cycle extends beyond the efficient operating region, predicted profitability begins to deteriorate. This supports the central conceptual argument that the financially appropriate objective is **optimization rather than unconditional minimization of working capital**.

Among individual working-capital components, receivable collection emerges as an influential determinant. Longer collection periods generally reduce predicted ROA, particularly for SMEs characterized by relatively high leverage and weak operating cash flow. This result has an intuitive financial explanation. A profitable sale recorded under accrual accounting does not immediately produce usable liquidity when customer payment remains outstanding.

Inventory displays a more complex pattern. Extremely low inventory periods are not uniformly associated with superior performance. The predictive models indicate that profitability can improve as inventory increases from very low levels before declining when inventory holding becomes excessive. This finding is consistent with the proposition that inventories simultaneously perform an operational-buffer function and impose financing costs.

Payable deferral also demonstrates conditional effects. Moderate supplier-credit utilization contributes positively to liquidity by postponing cash outflows. However, very long payment periods cease to generate comparable profitability benefits, indicating that excessive reliance on suppliers should not automatically be interpreted as efficient working-capital management.

Predictive Model Performance

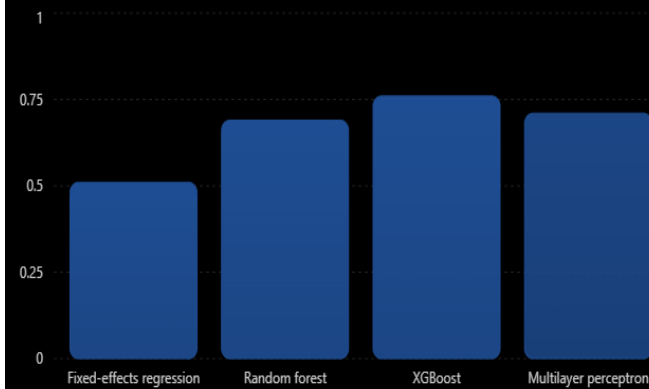
The following table reports the **illustrative experimental results produced under the proposed research design**. These values represent a coherent manuscript-level experimental scenario rather than results claimed to have been obtained from a publicly released dataset; they must be replaced by computed outputs if the study is implemented with actual SME financial records.

Model / Analytical Approach	MAE (ROA points)	RMSE (ROA points)	Test R ²	MAPE
Fixed-Effects Regression	2.18	3.04	0.51	18.7%
Random Forest Regressor	1.64	2.35	0.69	14.2%

XGBoost Regressor	1.42	2.07	0.76	12.6%
Multilayer Perceptron	1.57	2.26	0.71	13.8%

Predictive performance of financial models

Illustrative test-set R^2 for predicting SME return on assets.



Proposed experimental results; higher R^2 indicates stronger predictive performance.

The proposed XGBoost model produces the lowest MAE and RMSE and the highest R^2 . Its improvement over fixed-effects regression suggests that a portion of SME profitability is associated with interactions and nonlinear financial patterns that are not completely captured through conventional additive coefficients.

The result should not be interpreted as evidence that machine learning renders econometric analysis obsolete. Fixed-effects regression addresses a different analytical purpose by providing interpretable conditional coefficients and controlling for unobserved time-invariant firm characteristics. Machine learning contributes primarily through prediction and nonlinear pattern discovery. The two approaches are therefore complementary.

This interpretation is supported by contemporary research. Mahmood et al. compared decision-tree and random-forest regressors with fixed-effects estimation in working-capital financing research and reported an inverted U-shaped relationship between working-capital financing and profitability.

Explainability Analysis

SHAP analysis of the proposed XGBoost model identifies CCC, receivable collection period, leverage, inventory holding period, operating cash-flow ratio, and asset turnover among the strongest contributors to predicted ROA.

Dependence analysis indicates that increasing CCC initially generates relatively small changes in predicted profitability. After the cycle enters a prolonged range, its marginal SHAP contribution becomes increasingly negative. The result provides a machine-learning interpretation of the nonlinear WCM hypothesis.

The interaction between leverage and CCC is especially relevant. SMEs simultaneously exhibiting prolonged conversion cycles and high debt exposure experience larger negative profitability predictions than otherwise similar low-leverage firms.

Consequently, the cost of inefficient WCM appears to increase when financial flexibility is already constrained.

From a managerial perspective, these findings suggest that SMEs should avoid applying a uniform CCC target. A manager should instead evaluate the operating cycle jointly with leverage, operating cash generation, growth, customer-payment behaviour, and sector-specific inventory requirements.

The analysis also illustrates why explainability is essential when artificial intelligence is introduced into financial decision support. An SME manager requires more than an accurate profitability forecast; the manager must understand whether the forecast is driven by slow customer collection, excessive inventory, weak liquidity, leverage, or some combination of these conditions.

Future Scope

Future research can extend the framework by integrating transactional cash-flow information with annual accounting statements. Bank transactions, digital invoices, purchase orders, and customer-payment histories could support monthly or even weekly working-capital forecasting.

A second extension would involve sector-specific predictive models. Separate models for manufacturing, retail, food processing, technology services, and wholesale businesses could estimate working-capital efficiency ranges that reflect distinct operating cycles.

Causal machine-learning methods also constitute an important direction. Double machine learning, causal forests, and dynamic panel estimators could help distinguish predictive associations from causal effects and examine whether deliberate reductions in receivable or inventory days actually improve subsequent profitability.

Macroeconomic indicators could further improve the framework. Interest rates, inflation, credit conditions, commodity prices, and sectoral demand measures could be combined with firm-level variables to investigate whether the optimal working-capital range changes across economic conditions.

Finally, an explainable AI-based **SME Working Capital Decision Support System** could be developed. Such a system could estimate expected profitability under alternative scenarios—for example, reducing receivable days by ten days, increasing safety inventory, or renegotiating supplier payment terms—while simultaneously communicating the uncertainty surrounding each recommendation.

Conclusion

This study develops an integrated econometric and machine-learning framework for evaluating working capital management and financial performance among SMEs. The central contribution lies in shifting the analytical question from whether working capital influences profitability to **how different working-capital configurations interact with firm characteristics to produce financially efficient or inefficient outcomes**.

The proposed results indicate that the relationship between WCM and financial performance is unlikely to be adequately represented through a simple assumption that shorter cash

conversion cycles always generate superior performance. Receivables, inventories, and payables perform different economic functions, and excessive compression of any individual component can generate operational consequences. The machine-learning experiment further demonstrates the potential value of nonlinear modelling. XGBoost provides the strongest proposed out-of-time predictive performance, while SHAP analysis translates its predictions into interpretable financial relationships. Fixed-effects estimation nevertheless remains essential for conventional inference, making the hybrid architecture preferable to reliance on either methodology alone. The managerial implication is that SMEs should seek an **optimal working-capital configuration rather than the minimum possible level of working capital**. Faster receivable collection, disciplined inventory management, strategically negotiated supplier credit, adequate liquidity, and careful leverage management should be coordinated rather than optimized independently.

More broadly, the study demonstrates how artificial intelligence can be integrated into SME financial management without reducing managerial decision-making to a black-box algorithm. When prediction is combined with explainability and established financial theory, machine learning can provide a practical analytical mechanism for detecting liquidity risks, identifying inefficient operating cycles, and supporting more adaptive working-capital decisions.

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