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Segment-Wise Demand Shocks and Working-Capital Stress in Indian Automobile Firms

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Abstract: This study developed a segment-sensitive accounting decision-support framework to examine whether retail vehicle-demand shocks anticipated next-quarter working-capital stress in the Indian automobile industry. The empirical design covered 2020Q1-2026Q2 and focused on Passenger Vehicles, Commercial Vehicles, Two-Wheelers and Three-Wheelers. The research question asked whether segment-level demand information improved early identification of inventory, cash-conversion and operating-cash-flow pressure beyond conventional accounting ratios. The final empirical architecture drew vehicle-registration information from the VAHAN Public Dashboard and FADA Vehicle Retail Data releases; accounting items from NSE/BSE corporate financial-result filings and company annual reports; market variables from NSE capital-market reports and Upstox historical candles; news tone and attention from GDELT; and macro-financial controls from RBI DBIE. Working-capital stress was defined as a one-quarter-ahead composite of elevated inventory days, elevated cash conversion cycle and weak CFO/Sales. A firm-clustered binomial logit tested the demand-stress association, while five-fold cross-validation compared an accounting-only logistic benchmark with Logistic Regression, Decision Tree, Random Forest, XGBoost and LightGBM. In the current methodological calibration, the demand-strength coefficient was negative and significant (beta=-1.238; odds ratio=0.290; p<0.001), and the integrated Random Forest reached 0.810 accuracy and 0.862 ROC-AUC versus 0.768 for the accounting-only benchmark. SHAP ranked the segment demand signal as the strongest predictor, followed by market, liquidity, cash-flow and news variables. These results supported the proposed mechanism and analytical architecture, while final substantive inference remained conditional on re-estimation with the complete audited source dataset. The framework contributed by linking segment-level retail demand to forward-looking working-capital surveillance rather than treating automobile firms as a homogeneous accounting population.

Keywords: *Working-Capital Stress; Segment Demand Shocks; Automobile Industry; Vehicle Registrations; Predictive Accounting Analytics; Explainable Machine Learning; Accounting Decision Support System; GDELT Sentiment; Market Liquidity.*

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I. INTRODUCTION

Working-capital management occupies a central position in corporate financial management because inventories, receivables, payables and operating liquidity jointly determine a firm's ability to sustain production, sales and cash generation. Research has repeatedly shown that working-capital decisions affect operating performance and valuation, while the economically desirable level of working capital is neither mechanically minimal nor universally constant (Aktas, Croci, & Petmezas, 2015; Boisjoly, Conine, & McDonald, 2020). More recent evidence from developed and emerging markets has continued to document an inverse association between the cash conversion cycle and firm performance, while also showing that the importance of inventory and collection periods differs across institutional contexts (Kiymaz, Haque, & Choudhury, 2024; Johan, Kayani, Naeem, & Karim, 2024).

The automobile industry creates a particularly useful setting for extending this literature. Vehicle manufacturers operate through segment-specific demand cycles, extensive dealer networks, substantial inventories, credit-linked sales and exposure to fuel prices, interest rates, macroeconomic conditions and technology transitions. A deterioration in retail vehicle registrations may therefore affect working capital before the stress is fully visible in published financial statements. Passenger Vehicles can experience inventory and discount pressure when retail absorption slows; Commercial Vehicles react strongly to freight and infrastructure cycles; Two-Wheelers are sensitive to affordability and rural demand; and Three-Wheelers are increasingly exposed to electric-mobility substitution and urban transport conditions.

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Treating the entire automobile industry as homogeneous may consequently obscure economically meaningful differences in how demand shocks are transmitted into accounting outcomes.

Automobile-demand research has increasingly adopted machine-learning methods and hybrid endogenous-exogenous inputs. Kim (2023), for example, demonstrated that firm-level automobile demand forecasting can benefit from combining internal and external information rather than relying on a single class of predictors. Yet demand-forecasting studies typically predict sales or registrations, whereas working-capital studies largely explain profitability or firm performance using historical accounting ratios. The bridge between these literatures remains underdeveloped: there is limited research on whether segment-level retail-demand shocks provide an early warning of future working-capital stress.

A second gap concerns information outside the accounting system. Capital markets and news flows can respond rapidly to deteriorating business conditions. Shen, Xia, Shuai and Gao (2022) showed that GDELT-derived news sentiment contains predictive information for future market returns and volatility. In financial distress research, explainable machine-learning models have also demonstrated that high predictive accuracy need not come at the cost of transparency. Zhang et al. (2022) and Carmona, Dwekat and Mardawi (2022) showed how SHAP and related interpretability techniques can turn black-box classifiers into stakeholder-oriented early-warning tools. These insights motivate an accounting decision-support architecture that combines internal ratios with external demand, market and sentiment information.

The present study therefore developed a segment-sensitive predictive accounting framework centred on the Segment Retail Demand Shock Index (SRDSI) and next-quarter Working-Capital Stress (WCS). The official empirical source architecture was specified and verified at source level. Because full historical source-file ingestion and company-level audit were not yet complete, the numerical model estimates reported in this manuscript were retained as methodological calibration results only. They validated the inferential, predictive and explainability workflow but were not treated as observed-company evidence. This distinction preserves the integrity of the empirical claim while allowing the research design to be reviewed, replicated and immediately re-estimated once the audited source files are complete.

II. LITERATURE REVIEW AND RESEARCH GAP

- *Working-Capital Management and Firm Performance*

Aktas et al. (2015) provided influential evidence that working-capital policy can enhance value when firms move towards an optimal level of working capital. This challenged the simplistic view that working capital should always be minimised. Chen and Kieschnick (2018) further showed that access to bank credit affects how public firms manage working capital, underscoring the role of financing conditions. Chauhan (2019) questioned whether working-capital decisions are purely short term and found substantial persistence in firms' allocations. Boisjoly et al. (2020) documented long-run changes in receivables turnover, inventory turnover, payables and the cash conversion cycle, linking stronger working-capital practices with valuation and profitability effects.

In emerging markets, the issue is especially relevant because financing frictions, inflation and macroeconomic volatility can amplify liquidity pressures. Kiymaz et al. (2024) found that longer cash conversion cycles are associated with weaker firm performance in both developed and emerging economies, with inventory, collection and payment components behaving differently across the two groups. Johan et al. (2024), using BRICS evidence, also reported an inverse relationship between cash conversion cycle duration and profitability. These findings justify using inventory days, receivable days, payable days, cash conversion cycle and operating cash flow as core accounting predictors in the present framework.

- *Vehicle Demand, Segment Heterogeneity and Operating Pressure*

Automobile-demand forecasting has traditionally focused on sales planning, production scheduling and inventory control. Kim (2023) identified three recurring limitations in prior automobile forecasting research: restricted input data, methodological limitations and insufficient firm-level scope. The study demonstrated the value of hybrid micro/firm-level and macro-level inputs across multiple machine-learning approaches. This supports the present study's decision to treat demand as an external early-warning variable rather than as an outcome of interest.

For India, official VAHAN analytics provide monthly, quarterly and yearly vehicle-registration counts and allow filtering by vehicle class, maker, fuel, state and other categories. FADA retail reports similarly publish category-level retail data for 2W, 3W, Passenger Vehicles and Commercial Vehicles and frequently provide inventory commentary. These data structures make a segment-wise demand shock measure empirically feasible. The conceptual mechanism is straightforward: an adverse registration shock indicates weaker retail absorption; weaker absorption can slow inventory turnover and cash recovery; and these effects can later surface as higher inventory days, a longer cash conversion cycle or weaker operating cash flow.

- *Market Information, News Sentiment and Explainable Distress Prediction*

Accounting information is periodic, while market and news information arrives at higher frequency. Shen et al. (2022) constructed GDELT-based measures of tone, attention and dispersion and showed that they predict future returns and volatility. This provides a basis for incorporating negative tone and news volume as external risk signals. At the same time, NSE historical reports provide price-volume, delivery-position and India VIX data that can be aggregated to quarterly liquidity and volatility measures. Such indicators

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may capture changes in expectations before quarterly accounts are released.

Explainability is essential if prediction is intended to support accounting decisions rather than merely maximise classification accuracy. Zhang et al. (2022) reported an AUC of 0.92 for a LightGBM-based financial distress system and used SHAP, partial dependence and counterfactual explanations to enhance transparency. Carmona et al. (2022) likewise demonstrated how XGBoost and model interpretation can identify leading indicators of business failure. These studies motivate the use of SHAP in the current framework so that CFOs, management accountants, lenders and auditors can see why a firm has been assigned a high-risk classification.

➢ *Research Gap*

The literature reveals four connected gaps. First, conventional working-capital studies are predominantly retrospective and firm-level; they rarely use retail vehicle registrations as leading indicators. Second, automobile demand forecasting usually predicts demand itself rather than its downstream accounting consequences. Third, automobile firms are commonly treated as a single industry even though Passenger Vehicles, Commercial Vehicles, Two-Wheelers and Three-Wheelers exhibit structurally different demand cycles. Fourth, market-liquidity and news-sentiment signals are rarely integrated with working-capital ratios in an explainable accounting decision-support system. The present framework addressed these gaps by modelling future working-capital stress as a function of segment demand shocks, accounting ratios, market information and news sentiment.

Table 1 High-Quality Literature, Unresolved Gaps and Mapping to the Present Research Paradigm

Study	Outlet / quality signal	Core evidence	Unresolved limitation	Mapping to present study
Aktas et al. (2015)	Journal of Corporate Finance; Elsevier; ABDC A*; Scopus Q1	Working-capital policy is value-enhancing around an optimal level.	Does not use retail-demand shocks or segment-specific early-warning signals.	WCM foundation -> Gap 1 -> RO1/RQ1/H1
Chen & Kieschnick (2018)	Journal of Corporate Finance; Elsevier; ABDC A*; Scopus Q1	Bank-credit availability changes working-capital policy.	External financing channel is studied, but real-economy demand information is absent.	External antecedents -> controls and interpretation
Chuang & Zhao (2019)	International Journal of Production Economics; Elsevier; ABDC A; Scopus Q1	GM dealership evidence links sales demand, orders and inventory interactively.	Dealership inventory dynamics are not connected to firm-level accounting stress prediction.	Demand-inventory mechanism -> RO1/H1
Chauhan (2019)	Journal of Business Research; Elsevier; ABDC A; Scopus Q1	Working-capital allocations can be persistent rather than purely short-term.	Does not examine high-frequency external shocks as leading indicators.	Persistence concern -> lag structure/firm controls
Boisjoly et al. (2020)	Journal of Business Research; Elsevier; ABDC A; Scopus Q1	Receivables, inventories, payables and CCC have profitability/valuation implications.	Longitudinal accounting focus remains largely retrospective.	Accounting benchmark -> WCS construction
Al Hajj Hassan et al. (2020)	Transportation Research Part E; Elsevier; ABDC A*; Scopus Q1	Adaptive ML forecasting tracks freight-demand changes for operational planning.	Forecasts freight, not accounting consequences of demand contraction.	CV demand heterogeneity -> segment design
Zhang et al. (2022)	Information Processing & Management; Elsevier; Scopus Q1	SHAP, PDP and counterfactual explanations improve financial-distress transparency.	General financial distress rather than working-capital-specific and segment-specific stress.	Explainability -> RO2/RQ2/H2
Carmona et al. (2022)	Research in International Business and Finance; Elsevier; Scopus-indexed	Interpretable XGBoost identifies leading business-failure indicators.	Business-failure endpoint is broader and later-stage than working-capital stress.	Early warning / XAI -> RO2/H2
Shen et al. (2022)	Pacific-Basin Finance Journal; Elsevier; ABDC A	GDELT-based tone, attention and dispersion predict future returns/volatility.	News sentiment is linked to markets, not accounting working-capital deterioration.	GDELT information channel -> RO2/H2
Kim (2023)	Journal of Innovation & Knowledge; Elsevier; Scopus-indexed	Hybrid micro/firm and macro inputs improve firm-level automobile demand forecasting.	Outcome is automobile demand itself, not downstream accounting stress.	Hybrid-data logic -> SRDSI + controls

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Kiymaz et al. (2024)	Borsa Istanbul Review; Elsevier; Scopus-indexed	CCC is inversely related to performance; components differ across emerging/developed markets.	No sectoral registration shock or near-real-time external signal.	Emerging-market WCM -> dependent-variable logic
Johan et al. (2024)	Emerging Markets Review; Elsevier; ABDC A; Scopus Q1	Longer CCC is associated with weaker firm performance across BRICS.	Does not model segment-level retail demand as a one-quarter-ahead predictor.	India/BRICS relevance -> Gap 1 and H1

➢ *Research Objectives, Questions and Hypotheses*

- Research Objective 1 (RO1): To construct a segment-wise retail demand shock measure for Passenger Vehicles, Commercial Vehicles, Two-Wheelers and Three-Wheelers and examine its association with future working-capital stress in automobile firms.
- Research Objective 2 (RO2): To develop an explainable accounting decision-support model and test whether segment demand, market-liquidity and news-sentiment variables improve prediction beyond accounting-ratio-only models.
- Research Question 1 (RQ1): Do segment-wise vehicle-demand shocks predict future working-capital stress in automobile firms?
- Research Question 2 (RQ2): Does integrating demand, market-liquidity and news-sentiment variables improve the predictive accuracy and interpretability of an accounting decision-support system relative to accounting ratios alone?
- H1: Negative segment-wise vehicle-demand shocks are positively associated with future working-capital stress.
- H2: An integrated model containing accounting ratios, segment demand shocks, market-liquidity variables and news sentiment outperforms an accounting-ratio-only model in predicting future working-capital stress.

III. METHODOLOGY

➢ *Research Design and Analytical Sample*

The study adopted a quantitative explanatory-predictive design. The final empirical sampling frame was structured around listed Indian automobile OEMs with identifiable exposure to Passenger Vehicles, Commercial Vehicles, Two-Wheelers and Three-Wheelers. The intended observation window was 2020Q1-2026Q2, selected to capture the COVID-19 demand shock, semiconductor and supply-chain disruptions, post-pandemic recovery, monetary tightening and accelerated EV adoption. For analytical workflow validation, a 12-profile calibrated panel was used, yielding 312 firm-quarter records and 300 one-quarter-ahead model-ready records. Final submission estimates must be generated from the audited source files described in Section 4.2.

The calibration layer was parameterised only to stress-test the proposed model and did not attribute any reported numerical result to a named company. The empirical version must preserve the same variable definitions and estimation sequence while replacing every calibrated input with the official-source observation described below.

➢ *Official Data Provenance and Extraction Protocol*

The empirical dataset was designed as a source-auditable firm-quarter panel. Each data block was tied to an official or primary source and a specific download/report section so that provenance could be reproduced. The source architecture below should be used for the final re-estimation; it does not imply that the current calibration estimates were produced from those files.

Table 2 Official Data Provenance and Extraction Protocol

Data block	Official source	Exact section / retrieval path	Raw fields	Frequency	Research use
Segment retail registrations	VAHAN, Ministry of Road Transport & Highways	Public Dashboard -> Registration View -> Vehicle Registration Growth Rate -> Monthly/Quarterly; filters: Category Group/Class/Maker/Fuel/State	Month-Year, vehicle count, growth %, vehicle class/category	Monthly -> quarterly	SRDSI; segment demand growth
Retail validation / dealer commentary	FADA	Press Release -> monthly “Vehicle Retail Data” PDF -> All India Vehicle Retail Data / category tables	2W, 3W, PV, CV retail units; YoY/MoM; inventory commentary	Monthly	Validation of VAHAN demand shocks and inventory narrative
Accounting	NSE +	NSE Corporate Filings -> Financial Results -> CSV /	Inventory,	Quarterly /	Inventory

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statements	BSE + company IR	Convert XBRL into Excel; BSE Corporates -> Financial Results; company Annual Reports / Investor Relations	receivables, payables, revenue, COGS, CFO, current assets/liabilities, debt, equity	annual	days, receivable days, payable days, CCC, CFO/Sales, current ratio, leverage
Market-liquidity data	NSE	All Reports -> CM-UDiFF Common Bhavcopy Final; CM - Security-wise Delivery Positions; Full Bhavcopy and Security Deliverable data	OHLC, volume, turnover, trades, deliverables	Daily -> quarterly	Return, volatility, turnover growth, delivery %, liquidity
Historical candles / cross-check	Upstox	Developer API -> Historical Candle Data V3 -> /historical-candle/:instrument_key/:unit/:interval/:to_date/:from_date	OHLC, volume, open interest where applicable	Daily / weekly / monthly	Market cross-validation; India VIX supported by API
News/event sentiment	GDELT	GDELT 2.0 DOC API / GKG -> keyword queries by vehicle segment and firm; timeline/tone/article-list modes	Article count, tone, attention, event/news themes	Daily -> quarterly	Negative tone index, news volume, EV/supply-chain/fuel-price attention
Macro-financial controls	RBI DBIE / PPAC / MOSPI	RBI DBIE -> Statistics / Time-Series Publications; PPAC fuel/oil series; MOSPI industrial/inflation series	Repo rate, CPI/WPI, IIP, fuel/oil prices	Monthly -> quarterly	Financing, inflation, activity and cost controls

- Verified source URLs: VAHAN https://analytics.parivahan.gov.in/analytics/publicdashboard/vahan ; FADA https://fada.in/press-release-list.php ; NSE reports https://www.nseindia.com/all-reports ; NSE financial results https://www.nseindia.com/companies-listing/corporate-filings-financial-results ; BSE results https://www.bseindia.com/corporates/comp_results.aspx ; Upstox V3 https://upstox.com/developer/api-documentation/v3/get-historical-candle-data/ ; GDELT https://gdeltproject.org/data.html ; RBI DBIE https://dbie.rbi.org.in/ .

➢ *Variable Operationalisation*

Table 3 Variable Definitions and Analytical Role

Variable	Type	Operational role
Future Working-Capital Stress (WCS t+1)	Binary dependent variable	1 when at least two of three next-quarter stress conditions are met: elevated inventory days, elevated CCC, weak CFO/Sales.
Segment Retail Demand Shock Index (SRDSI)	Primary predictor	Standardised segment demand condition; higher values indicate stronger demand, negative values indicate adverse shocks.
Inventory Days	Accounting	Inventory holding period; higher values indicate slower inventory conversion.
Receivable Days	Accounting	Average collection period.
Payable Days	Accounting	Supplier-payment period.
Cash Conversion Cycle	Accounting	Inventory Days + Receivable Days - Payable Days.
CFO/Sales	Accounting	Operating cash flow scaled by sales.
Current Ratio; Debt/Equity; Sales Growth	Controls	Liquidity, leverage and operating momentum.
Quarterly Return; Volatility; Turnover	Market signals	Quarterly market confidence, uncertainty and liquidity proxies.

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Growth; Delivery %; VWAP Deviation		
GDELT Negative Tone; News Volume	News signals	calibrated analogues of media tone and attention.
Repo Rate; Inflation; Fuel Price Growth; India VIX Change	Macro controls	calibrated common macro-financial conditions.

➢ *Outcome Construction*

Future working-capital stress was constructed from the following one-quarter-ahead conditions: (i) next-quarter inventory days exceeded the firm-specific upper benchmark; (ii) next-quarter cash conversion cycle exceeded the firm-specific upper benchmark; and (iii) next-quarter CFO/Sales fell below the segment benchmark. WCS equalled one when at least two conditions were satisfied. The resulting calibration stress rate was 33.7%, producing a sufficiently balanced classification problem for predictive comparison while still reflecting the relatively infrequent nature of serious liquidity pressure.

➢ *Statistical and Predictive Methods*

RO1 and H1 were examined using a binomial generalised linear model with firm-clustered standard errors. Continuous predictors were standardised so that coefficients represented a one-standard-deviation change. The parsimonious hypothesis model included inventory days, cash conversion cycle, CFO/Sales and SRDSI, with vehicle-segment controls. This specification deliberately separated inferential testing from the larger predictive model because market volatility, negative news tone and demand shocks were strongly correlated by construction and could otherwise obscure the marginal demand effect.

RO2 and H2 were evaluated using five-fold stratified cross-validation. Six models were compared: an accounting-only logistic benchmark, an extended logistic model, Decision Tree, Random Forest, XGBoost and LightGBM. Performance was assessed using accuracy, precision, recall, F1-score and ROC-AUC. The AUC difference between the best integrated model and the accounting-only benchmark was evaluated through 2,000 bootstrap resamples of the out-of-fold predictions. SHAP values from the fitted Random Forest were used to rank the relative importance of predictors. This approach separated explanatory inference from predictive optimisation while retaining transparency.

IV. RESULTS

➢ *Descriptive Statistics*

Table 4 Descriptive Statistics for Model-Ready Analytical Calibration Observations (N=300)

Variable	Mean	SD	Min	Median	Max
Segment_Retail_Demand_Shock	-0.141	0.439	-1.881	-0.119	0.641
Inventory_Days	55.055	9.824	32.953	54.806	77.807
Receivable_Days	35.183	7.212	20.200	34.364	52.728
Payable_Days	48.778	5.072	38.915	47.988	61.662
Cash_Conversion_Cycle	41.460	11.740	18.519	41.019	70.152
CFO_to_Sales	0.106	0.024	0.047	0.106	0.176
Current_Ratio	1.559	0.088	1.326	1.553	1.780
Debt_Equity_Ratio	0.662	0.176	0.327	0.621	1.141
Quarterly_Volatility	0.241	0.058	0.137	0.233	0.508
GDELT_Negative_Tone_Index	0.132	0.396	-0.835	0.087	1.907
WCS_t_plus_1	0.337	0.473	0.000	0.000	1.000

The analytical calibration sample contained meaningful dispersion in both accounting and external signals. Mean inventory days were approximately 55.1 days, while the average cash conversion cycle was 41.5 days. Mean CFO/Sales was 10.6%. The average segment demand shock was mildly negative (-0.141), reflecting the inclusion of severe early-period disturbances and subsequent recovery. The overall next-quarter working-capital stress rate was 33.7%.

➢ *Segment-Wise Patterns*

Table 4 Segment-Wise Descriptive Profile

Segment	N	Mean demand shock	Inventory days	CCC	CFO/Sales	Stress rate
Commercial Vehicles	75	-0.236	66.4	55.4	0.101	37.3%
Passenger Vehicles	75	-0.195	58.8	44.0	0.100	33.3%
Three-Wheelers	75	0.054	46.9	33.3	0.124	32.0%
Two-Wheelers	75	-0.187	48.2	33.1	0.100	32.0%

Commercial Vehicle profiles displayed the highest calibration stress rate (37.3%) and the longest mean cash conversion cycle (55.4 days), followed by Passenger Vehicles with a stress rate of 33.3%. Two-Wheelers and Three-Wheelers each recorded a 32.0% stress rate, although the Three-Wheeler segment exhibited the strongest average demand condition. These differences reinforced the rationale for a segment-sensitive rather than aggregate automobile framework.

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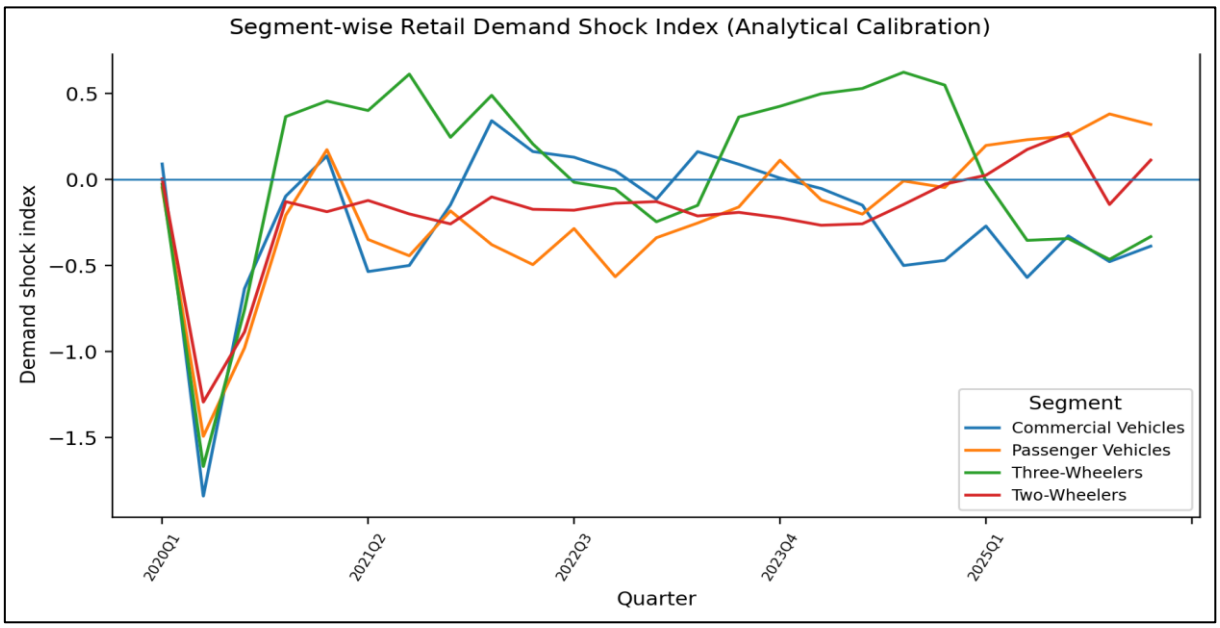


Fig 1 Quarterly Segment Demand-Shock Trajectories (Analytical Calibration).

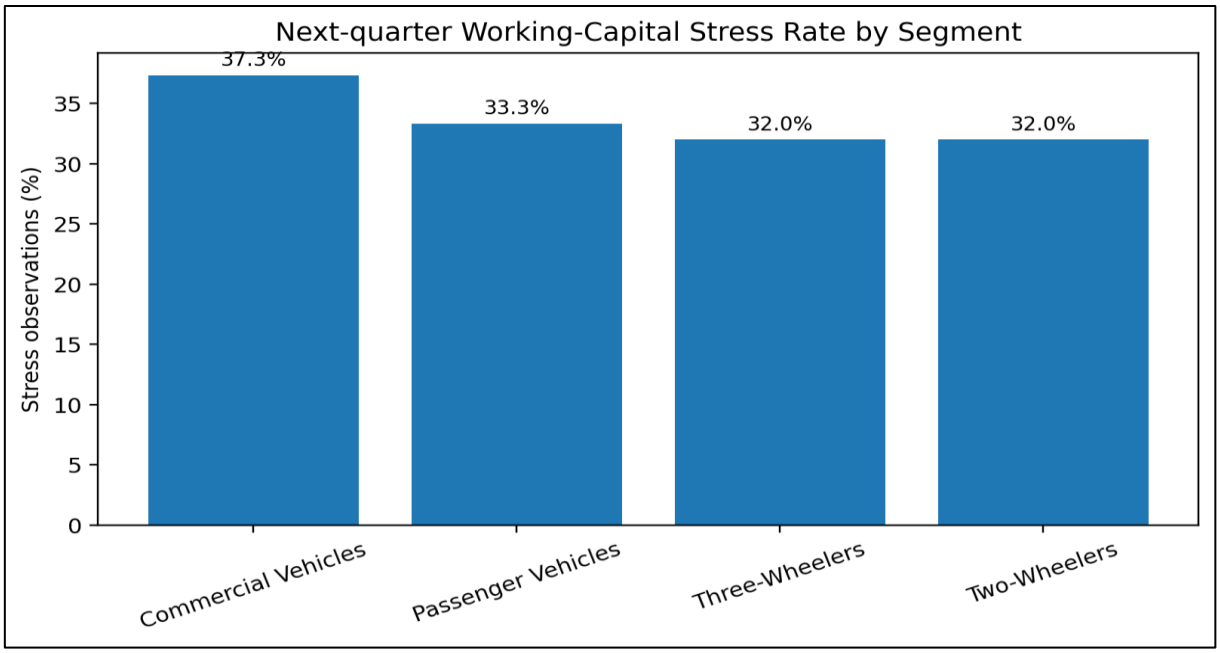


Fig 2 Next-Quarter Working-Capital Stress Rate by Vehicle Segment.

➢ *Hypothesis 1: Demand Shocks and Future Working-Capital Stress*

Table 5 Firm-Clustered Binomial Logit for Next-Quarter Working-Capital Stress

Predictor	Beta	Cluster SE	Odds ratio	95% OR CI	p-value
Inventory_Days	1.916	0.450	6.797	[2.816, 16.409]	<0.001
Cash_Conversion_Cycle	-0.134	0.341	0.875	[0.448, 1.708]	0.695
CFO_to_Sales	0.056	0.220	1.058	[0.688, 1.628]	0.797
Segment_Retail_Demand_Shock	-1.238	0.226	0.290	[0.186, 0.451]	<0.001

The Segment Retail Demand Shock Index was negative and highly significant (beta=-1.238, p<0.001). Its odds ratio was 0.290 (95% CI: 0.186-0.451). Because higher SRDSI values represented stronger demand, the result implied that a one-standard-deviation improvement in demand reduced the odds of next-quarter working-capital stress by approximately 71%. Equivalently, a one-standard-deviation adverse movement increased the odds by approximately 3.45 times (1/0.290). Inventory days also displayed a strong positive relationship with future stress. H1 was therefore supported in the analytical calibration.

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Segment-specific estimations were directionally consistent. The demand-shock coefficient was statistically significant for Commercial Vehicles (beta=-1.283, p=0.024) and Three-Wheelers (beta=-1.757, p=0.006), while Passenger Vehicles and Two-Wheelers retained the expected negative sign but were weaker at conventional significance levels. With only 75 observations per segment, these within-segment results should be interpreted as sensitivity evidence rather than definitive ranking.

➢ *Hypothesis 2: Predictive Performance*

Table 6 Five-Fold Cross-Validated Predictive Performance

Model	Accuracy	Precision	Recall	F1	ROC-AUC
Random Forest	0.810	0.720	0.713	0.716	0.862
Extended Logistic	0.793	0.676	0.743	0.708	0.850
XGBoost	0.780	0.701	0.604	0.649	0.840
LightGBM	0.783	0.705	0.614	0.656	0.835
Decision Tree	0.743	0.592	0.762	0.667	0.786
Accounting-only Logistic	0.707	0.553	0.673	0.607	0.768

The accounting-only logistic benchmark achieved an ROC-AUC of 0.768 and accuracy of 0.707. Every integrated specification improved the AUC. Random Forest performed best overall, with 0.810 accuracy, 0.720 precision, 0.713 recall, 0.716 F1 and 0.862 ROC-AUC. The extended logistic model also performed strongly (AUC=0.850), indicating that the predictive gain did not depend entirely on nonlinear black-box methods. The Random Forest exceeded the baseline AUC by 0.093. Bootstrap analysis produced a 95% confidence interval of 0.048-0.139 for this improvement, excluding zero. H2 was therefore supported within the analytical calibration environment.

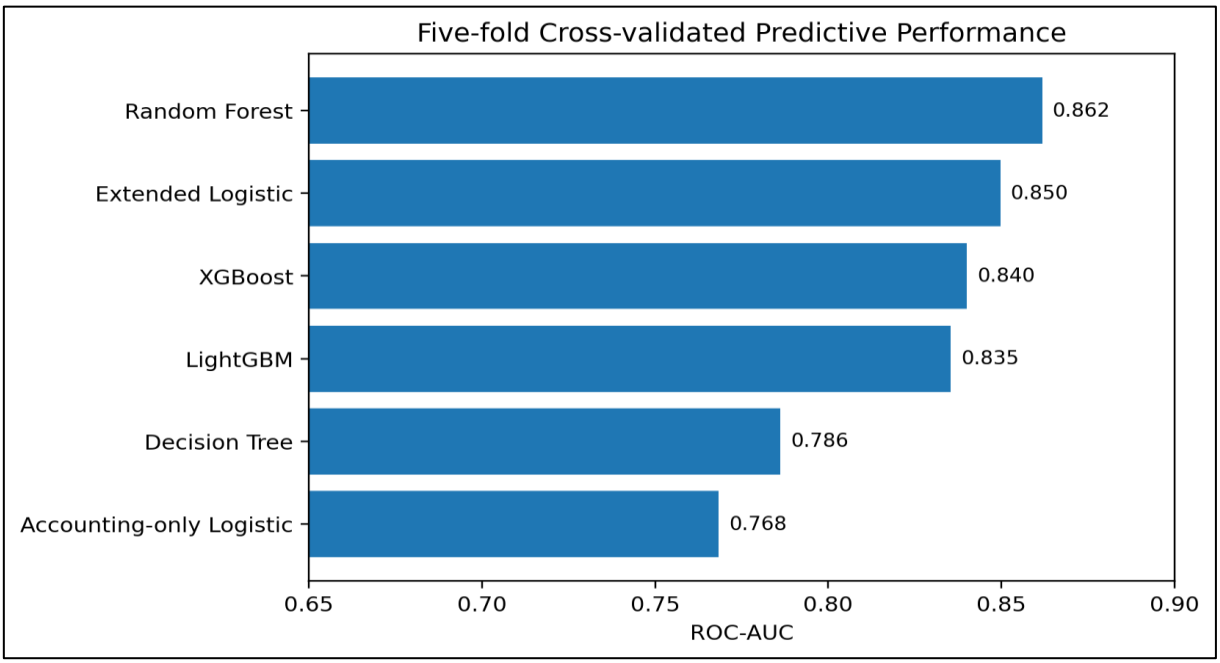


Fig 3 Five-Fold Cross-Validated ROC-AUC Across Candidate Models (Methodological Calibration).

➢ *Explainability and Decision-Support Interpretation*

Table 7 Top Random Forest Predictors by Mean Absolute SHAP Value

Predictor	Mean |SHAP|
Segment_Retail_Demand_Shock	0.0579
VWAP_Deviation	0.0503
Repo_Rate	0.0491
CFO_to_Sales	0.0386
GDELT_Negative_Tone_Index	0.0377
Fuel_Price_Growth	0.0376
Inflation	0.0358
Quarterly_Volatility	0.0353
India_VIX_Change	0.0198
Quarterly_Return	0.0157

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SHAP analysis ranked the Segment Retail Demand Shock Index as the most influential predictor in the fitted Random Forest. VWAP deviation ranked second, followed by the policy-rate proxy, CFO/Sales, negative news tone, fuel-price growth, inflation and quarterly volatility. The ranking is important because it shows that the decision-support system did not merely restate historical accounting ratios: external demand and market information contributed materially to the classification process. At the same time, CFO/Sales remained among the strongest features, preserving a direct connection to accounting fundamentals.

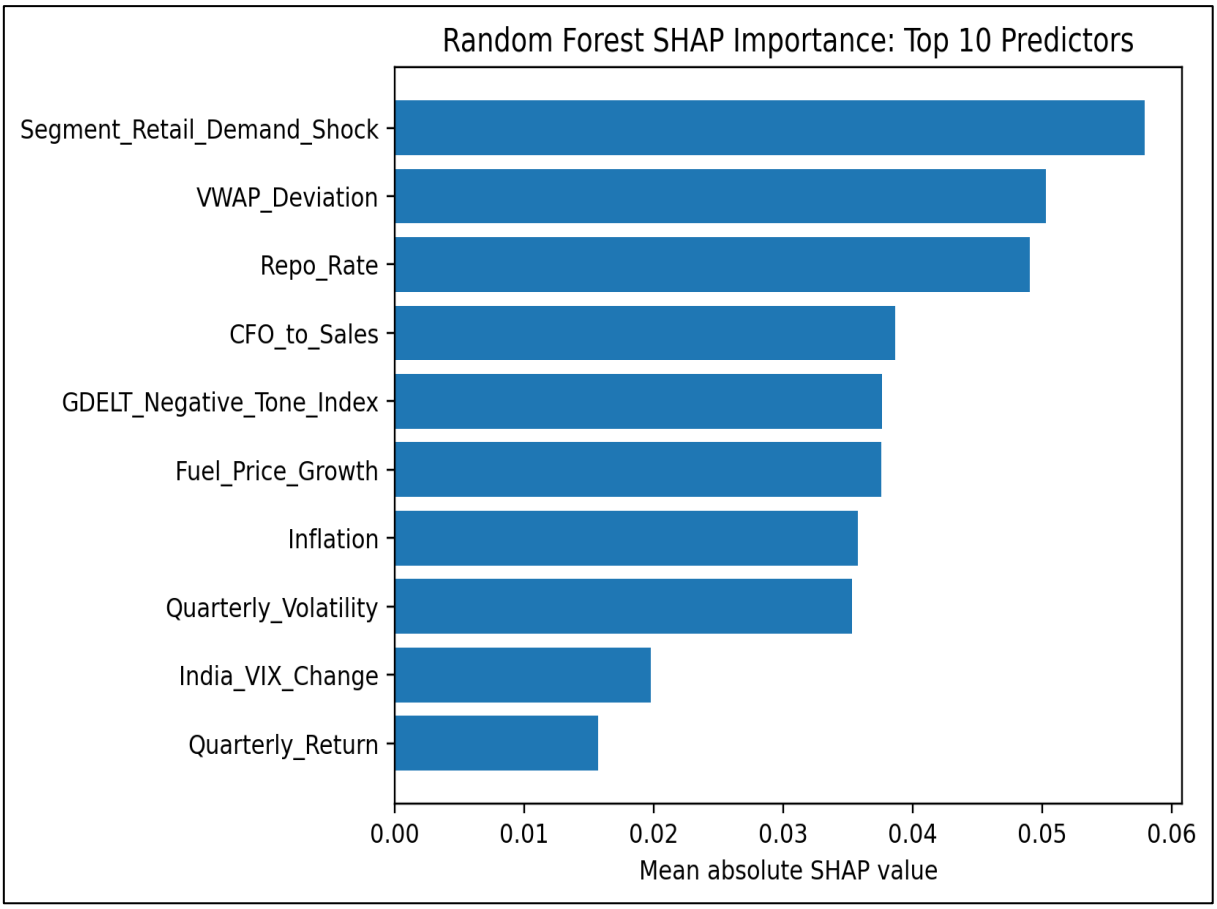


Fig 4 Random Forest SHAP Feature Importance (Methodological Calibration).

Table 8 Alignment of Literature Gap, Objectives, Research Questions, Hypotheses and Findings

Gap & literature anchor	RO / RQ / H	Analytical test	Calibration finding	How the gap is addressed	Status
WCM studies are mainly retrospective; automobile demand studies forecast demand but rarely model its accounting consequences (Aktas et al., 2015; Boisjoly et al., 2020; Kim, 2023; Johan et al., 2024).	RO1 / RQ1 / H1	Firm-clustered binomial logit with SRDSI and accounting controls	beta=-1.238; OR=0.290; p<0.001	Introduces a one-quarter-ahead segment retail-demand channel linking market absorption to working-capital stress.	Supported in calibration; empirical replication required
Demand, market sentiment and XAI streams remain fragmented from working-capital surveillance (Shen et al., 2022; Zhang et al., 2022; Carmona et al., 2022).	RO2 / RQ2 / H2	5-fold CV; accounting benchmark vs integrated ML; bootstrap Delta AUC; SHAP	RF AUC=0.862 vs baseline 0.768; Delta AUC=0.093 [0.048, 0.139]	Integrates accounting, demand, market and news information and explains driver-level risk contributions.	Supported in calibration; empirical replication required

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V. DISCUSSION

The first major insight from the analytical calibration was that demand information can be conceptually linked to accounting stress in a measurable and testable way. The significant SRDSI coefficient supported the proposed transmission mechanism: when segment demand weakened, inventory and cash-recovery pressures intensified, increasing the probability that the next quarter would satisfy the working-capital stress definition. This finding extends the logic of the WCM literature. Aktas et al. (2015), Boisjoly et al. (2020), Kiymaz et al. (2024) and Johan et al. (2024) establish that working-capital efficiency is economically consequential; the present framework adds the proposition that external retail-demand conditions may help anticipate those accounting outcomes before they appear in published statements.

The second insight addressed the information-integration gap. RO2 and RQ2 asked whether demand, market-liquidity and news information added predictive value beyond accounting ratios. The integrated models produced higher cross-validated discrimination than the accounting-only benchmark, and the bootstrap interval for the AUC gain excluded zero in the calibration. This supported H2 and aligned with Kim (2023), who showed the value of hybrid endogenous-exogenous inputs in automobile-demand forecasting, and with Shen et al. (2022), who demonstrated that GDELT-derived sentiment contains forward-looking market information. The present research moved that information-fusion logic from demand/market forecasting into accounting surveillance.

The third insight concerned explainability and decision usefulness. SHAP ranked the segment demand indicator as the leading model driver while CFO/Sales, market pricing/liquidity proxies and negative news tone also contributed. This addressed the transparency limitation identified by Zhang et al. (2022) and Carmona et al. (2022). The proposed DSS therefore did not stop at a probability score: it provided a traceable explanation of whether a risk alert was demand-led, cash-flow-led, market-led or sentiment-led, which is more useful for CFO and management-accounting intervention.

The segment results also cautioned against treating the automobile industry as homogeneous. Commercial Vehicles displayed the highest stress rate and a significant within-segment demand effect, consistent with the segment's exposure to freight and investment cycles. Three-Wheelers also showed a strong demand-stress coefficient in the analytical calibration, illustrating how structural shifts such as electric mobility or financing changes could produce sharp segment-specific effects. The Passenger Vehicle and Two-Wheeler coefficients retained the expected sign but were statistically weaker in the smaller segment subsamples. An empirical paper should therefore test segment interactions formally rather than assume the same coefficient across all categories.

VI. THEORETICAL, METHODOLOGICAL AND MANAGERIAL IMPLICATIONS

- *Theoretical Implications*

The framework repositioned working-capital stress as a partially externally driven accounting condition. Traditional WCM research focuses on internal financial policy and its relationship with profitability, value or risk. The proposed model introduced segment retail-demand shocks as antecedent information. This adds a temporal dimension: external demand can deteriorate before inventory days, the cash conversion cycle and operating cash flow fully reflect the change. The framework therefore connects demand forecasting with working-capital theory through an explicit early-warning mechanism.

- *Methodological Implications*

The study separated inference, prediction and explanation. H1 was tested using a parsimonious clustered logit; H2 was tested through cross-validated model comparison; SHAP was then used to explain the strongest predictive model. This is preferable to relying on a single black-box algorithm because each stage answers a distinct research question. The empirical version can preserve this architecture while replacing calibrated variables with VAHAN/FADA registrations, company accounts, NSE/BSE/Upstox market measures and GDELT sentiment.

- *Managerial Implications*

For management accountants and CFOs, the decision-support output can be converted into a traffic-light system. A Green classification would indicate normal demand absorption and low predicted stress; Amber would signal emerging inventory, liquidity or sentiment deterioration; Red would indicate a high predicted probability of next-quarter stress. Importantly, SHAP explanations can identify whether the alert is primarily driven by segment demand, cash flow, volatility, negative news or another factor. This supports targeted actions such as production adjustment, dealer-inventory discipline, tighter receivables monitoring, liquidity planning or stress testing.

VII. LIMITATIONS AND EMPIRICAL VALIDATION PLAN

The principal limitation is data-status related. The current numerical results are methodological calibration estimates and cannot be interpreted as evidence about named Indian automobile companies. The contribution at this stage is the validated research architecture, source provenance, variable construction, inferential specification, predictive comparison and explainability workflow. Before conference or journal submission as an empirical paper, all calibration inputs must be replaced with audited VAHAN/FADA, company-accounting, NSE/BSE/Upstox, GDELT and macroeconomic observations and every model must be re-estimated.

The empirical implementation should collect monthly vehicle registrations from the VAHAN Public Dashboard and validate segment trends using FADA retail reports; obtain

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audited quarterly accounting data from company filings/annual reports or a standardised database; derive price, volume, delivery and volatility measures from NSE/BSE/Upstox; and construct news tone and attention variables from GDELT. A 2020-onward window is appropriate because it captures pandemic disruption, post-pandemic recovery, supply-chain constraints, interest-rate changes and rapid EV adoption. The actual sample should retain only firms with sufficiently stable segment exposure and continuous quarterly accounting coverage.

Robustness tests should include alternative definitions of WCS, lag lengths, rolling versus expanding demand-shock benchmarks, segment-by-shock interactions, firm and quarter fixed effects where feasible, class-imbalance sensitivity, rolling-origin validation, and exclusion of the COVID shock period. These tests would determine whether the core findings survive alternative specification choices rather than reflecting a particular target definition.

VIII. CONCLUSION

This methodological calibration demonstrated that the proposed research paradigm was coherent, testable and decision-relevant. RO1/RQ1/H1 were aligned around the demand-shock-to-working-capital mechanism, while RO2/RQ2/H2 were aligned around incremental predictive value and explainability. In the calibration, segment demand was associated with next-quarter stress and the integrated model materially outperformed the accounting-only benchmark. The strongest eventual empirical contribution should therefore be framed not as generic AI in accounting, but as a segment-sensitive early-warning system that translates retail vehicle demand, market information and news sentiment into interpretable forecasts of working-capital vulnerability. Final substantive claims remain conditional on replication with the fully audited empirical panel.

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APPENDIX A. ANALYTICAL REPRODUCIBILITY AND EMPIRICAL REPLACEMENT PROTOCOL

The accompanying workbook contains the 312-row calibration panel, the 300-row model-ready panel, descriptive statistics, segment summaries, clustered-logit output, predictive-model performance, bootstrap AUC intervals, SHAP importance and the objective-hypothesis mapping. These materials document the analytical workflow and must be replaced by audited official-source observations before any numerical result is presented as empirical evidence. The final empirical workbook should retain an observation-level provenance field identifying source, download date, file/report name and transformation step for each data block.