© AUG 2026 | IRE Journals | Volume 10 Issue 2 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I2-1722411

Data-Driven Financial Reporting and Forecasting for Small and Mid-Sized Enterprises: A Practical Framework for Decision-Ready Accounting Analytics

ASHLEY MUNASHE SHAMBARE[1], NELIA MLAMBO[2], MELODY RACHAEL CHITUKUTUKU[3], DELINE KUFANDADA[4], MUNASHE NAPHTALI MUPA[5],

[1]*Bentley University, ORCiD: 0009-0003-8458-1825*

[2]*University of Northern Iowa, ORCiD: 0009-0002-6348-8560*

3American University, ORCiD: 0009-0003-4780-4540

[4]*Illinois State University, ORCiD: 0009-0009-3675-4959*

[5]*Hult International Business School, ORCiD: 0000-0003-3509-861X*

***Abstract-** This study develops and empirically illustrates a practical accounting-analytics framework for improving the quality, timeliness, and decision usefulness of financial reporting and short-horizon forecasting in small and mid-sized enterprises (SMEs). The paper responds to a persistent challenge in the SME literature: many firms operate with fragmented transaction records, limited management-accounting adoption, weak reconciliation discipline, and highly reactive budgeting routines, even though they face acute pressure to make fast, informed operating decisions. Using the Online Retail II transaction dataset accessed through Kaggle and originally archived by the UCI Machine Learning Repository the study constructs a decision-ready reporting layer based on gross revenue, returns, net revenue, order activity, customer activity, concentration patterns, and short-term forecast baselines. A cleaned sample of 1,041,670 positive sales rows and 19,494 cancellation/return rows was aggregated into a 24-month management dashboard and tested with simple forecast models appropriate for SME settings. The results show pronounced seasonality, material return-rate variation, and strong associations between net revenue and operational demand indicators such as orders and active customers. A Holt linear model produced the best out-of-sample performance over the last six months of the sample, with a MAPE of 11.47%, outperforming both a naïve benchmark and a trailing moving-average approach. The paper translates these findings into a five-layer framework covering transaction capture and reconciliation, diagnostic reporting, liquidity visibility, rolling forecasting, and governance cadence. The contribution is therefore both analytical and practical: it shows how SME finance functions can move from static compliance reporting toward integrated, decision-ready accounting analytics without requiring overly complex systems.*

***Keywords:** SMEs; financial reporting; forecasting; management accounting; dashboard analytics; liquidity monitoring; variance analysis.*

I. INTRODUCTION

capabilities of management accountants materially influence decision quality. For SMEs, the implication is clear: the issue is not whether accounting data exist, but whether finance functions can structure them into a disciplined cycle of reconciliation, interpretation, variance review, and action.

Digital tools have made that transition more feasible. Cloud accounting, dashboard platforms, and business intelligence architectures can reduce lag, automate reconciliations, and improve visibility across revenue, cost, and working-capital drivers (Sastararuji et al., 2022; Gonçalves et al., 2023). However, adoption is uneven, and SMEs still lag in digital transformation because of cost, skill shortages, and limited internal capacity (OECD, 2024). At the same time, tighter financing conditions have increased the cost of managerial error. OECD (2024) reports that higher borrowing costs and weaker lending conditions have materially constrained SMEs’ access to finance, increasing the need for stronger internal planning, earlier warning signals, and better cash visibility.

© AUG 2026 | IRE Journals | Volume 10 Issue 2 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I2-1722411

Recent practitioner-oriented studies have begun to address this gap. Ayankoya et al. (2025) propose a framework for data-driven SME financial optimisation, while Nhemachena et al. (2026) emphasise budget control, receivables visibility, and accounting analytics for U.S. small businesses. Even so, a tighter articulation is still needed around how SME finance teams can connect transaction-level data, exception detection, dashboard logic, variance analysis, and short-horizon forecasting into one integrated operating model. This paper responds to that need.

The objective of the study is to develop a practical framework for decision-ready accounting analytics in SMEs and to illustrate its operation using a large transaction dataset. Three research questions guide the paper: (1) Which reporting indicators are most useful for converting raw SME transaction data into management-ready financial visibility? (2) How can variance analysis and simple forecasting methods improve forward-looking control without excessive analytical complexity? and (3) What operating framework best links reconciliations, dashboard monitoring, liquidity awareness, and decision governance in SME settings?

II. LITERATURE REVIEW

The literature on SME finance and management accounting consistently shows that smaller firms face a dual problem: they require timely financial insight, but they often lack the organisational infrastructure to generate it reliably. Ylä-Kujala et al. (2023) find that up to 78% of small businesses report management-accounting challenges linked to systems, personnel, or organisational limitations, and that these pressures can motivate firms to adopt more formal accounting practices. This insight is important because it reframes SME accounting not as a scaled-down version of large-firm accounting, but as a resource-constrained process requiring selective, high-impact analytics.

The data analytics literature strengthens that argument. Franke and Hiebl (2023) show that data quality and the analytics capabilities of management accountants enhance organisational decision quality, particularly when firms are trying to make value from broader data ecosystems. In practice, this means that SME reporting quality depends not only on software adoption, but also on finance personnel being able to interpret patterns, communicate findings, and embed analytics into operational decisions.

Cloud accounting and digital reporting platforms have therefore become increasingly prominent in SME research. Sastararuji et al. (2022) show that cloud accounting can support more timely and accessible financial information in SMEs, especially when remote access, automation, and integrated workflows matter. Gonçalves et al. (2023) further demonstrate that business intelligence platforms can integrate disparate datasets into dashboards that improve interpretability, reduce information overload, and support more efficient management responses. From a reporting standpoint, the significance of these systems lies in their ability to combine ETL discipline, KPI design, visualisation, and threshold alerts into one decision environment.

Forecasting adds a forward-looking dimension to this reporting architecture. Jenčová et al. (2025) show that even relatively standard time-series techniques can provide useful forward estimates for financial indicators in wholesale and retail settings. In parallel, the SME failure-prediction literature underscores the value of financial ratios, trend signals, and early-warning analysis for anticipating operational strain and credit deterioration (Ciampi et al., 2021; Wang and Guedes, 2025). The implication for SMEs is that forecasting need not be overly sophisticated to be useful; what matters is consistent model use, transparent assumptions, and disciplined comparison between expected and actual outcomes.

Finally, governance and control remain essential. Netshifhefhe et al. (2024) argue that stronger audit-informed processes and investigative control logic can reinforce reporting integrity, compliance, and accountability. For SMEs, this does not necessarily imply full forensic audit capability. Rather, it suggests that exception detection, reconciled records, and documented review trails materially improve the credibility and usefulness of financial information.

© AUG 2026 | IRE Journals | Volume 10 Issue 2 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I2-1722411

Taken together, the literature points to five consistent themes: data quality matters; management-accounting adoption in SMEs is uneven; dashboards improve interpretation when they are role-relevant; forecasting can improve resilience when embedded into routine review cycles; and governance discipline remains foundational. The gap addressed in this paper lies in integrating these themes into a practical, decision-ready accounting framework with an empirical illustration.

III. METHODOLOGY

This study adopts an applied analytics design that combines literature synthesis with empirical demonstration. The aim is not to estimate causal effects for the entire SME universe, but to show how transaction-level data can be transformed into a management accounting system that improves reporting visibility and short-horizon forecasting.

The empirical illustration uses the Online Retail II dataset, accessed through Kaggle and originally published by the UCI Machine Learning Repository (Kaggle, n.d.; Chen, 2012). The dataset contains two years of transactional retail records and is suitable for demonstrating the reporting layer of an SME-style analytics environment because it provides invoice identifiers, dates, quantities, prices, customers, and geographic information at high volume. While it does not contain a complete general ledger, bank statement, or payables sub-ledger, it is sufficiently rich to test sales-side reporting, exception handling, customer activity monitoring, concentration analysis, and short-horizon revenue forecasting.

Data preparation followed five steps. First, both annual worksheets were merged into a single transaction file. Second, invoice dates were converted into a consistent datetime format and transaction revenue was computed as quantity multiplied by unit price. Third, cancellation and return records were identified using credit-note style invoice prefixes and negative transaction values. Fourth, the sales-side analytical sample was restricted to positive-price, positive-quantity, non-cancelled transactions for core revenue analysis. Fifth, monthly management indicators were constructed for a complete 24-month window from December 2009 to November 2011, thereby excluding the final partial month from model estimation.

The study computes six core management indicators: net revenue, orders, active customers, average order value, return rate, and revenue per customer. Net revenue is defined as gross positive sales less the absolute value of cancellations and returns. Orders are measured as unique invoices. Active customers are measured as unique non-null customer identifiers per month. Average order value is gross revenue divided by orders. Return rate is returns value divided by gross revenue. Revenue per customer is gross revenue divided by active customers. These indicators were selected because they jointly capture operational volume, quality of revenue, customer activity, and income concentration.

To operationalise variance logic, the study compares actual monthly net revenue against a trailing three-month baseline, thereby approximating the type of rolling benchmark often used in smaller firms where fully modelled budgets are not always available. For short-horizon forecasting, three parsimonious models were tested on a hold-out sample comprising the last six full months of the dataset: a naïve last-period model, a trailing three-month moving average, and a Holt linear model with damped trend. Forecast accuracy was assessed using mean absolute error (MAE), root mean squared error (RMSE), and mean absolute percentage error (MAPE).

Table 1. Dataset preparation and analytical sample summary.

Metric	Value
Raw transaction rows	1,067,371
Rows with positive price	1,061,164
Positive-sales rows used for core sales analysis	1,041,670
Cancellation/return rows	19,494
Unique invoices (all records)	53,628
Positive-sales invoices	40,077
Countries represented	43
Rows with known customer ID in positive-sales sample	77.3%
Complete monthly analysis window	24 months (Dec 2009-Nov 2011)

© AUG 2026 | IRE Journals | Volume 10 Issue 2 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I2-1722411

IV. RESULTS

4.1 Reporting visibility and data quality

Table 1 shows that the raw dataset contained 1,067,371 transaction rows. After isolating positive-price records and excluding cancellation/return lines from the core sales sample, the reporting layer was built on 1,041,670 positive-sales rows and 19,494 cancellation/return rows. The sample spans 43 countries, although only 77.3% of positive-sales rows contain a known customer identifier. This matters from a reporting standpoint because transaction completeness does not automatically imply customer-analytics completeness. An SME adopting this framework would therefore need to treat customer master-data quality as a control objective in its own right.

Across the 24 complete months, mean monthly net revenue was 792,161.13, mean monthly orders were 1,636, and mean monthly active customers were 1,041. Net revenue reached its highest point in November 2011 (1,461,756.25) and its lowest point in April 2011 (493,207.12). The highest return-rate month was January 2011, where returns represented 19.00% of gross revenue. These swings reinforce the argument that monthly revenue alone is an insufficient reporting indicator; managers also need contemporaneous visibility over returns, order volume, and customer activity.

Table 2. Descriptive statistics for core monthly dashboard indicators (Dec 2009-Nov 2011).

Statistic	Net revenue	Orders	Active customers	Average order value	Return rate (%)	Revenue per customer
Mean	792,161.13	1,635.75	1,040.83	516.53	6.64	810.28
Median	687,195.10	1,531.00	960.50	494.72	5.97	773.60
Minimum	493,207.12	1,086.00	720	425.58	3.13	628.28
Maximum	1,461,756.25	2,769.00	1,664.00	809.88	19	1,426.67

Figure 1. Monthly net revenue and return rate.

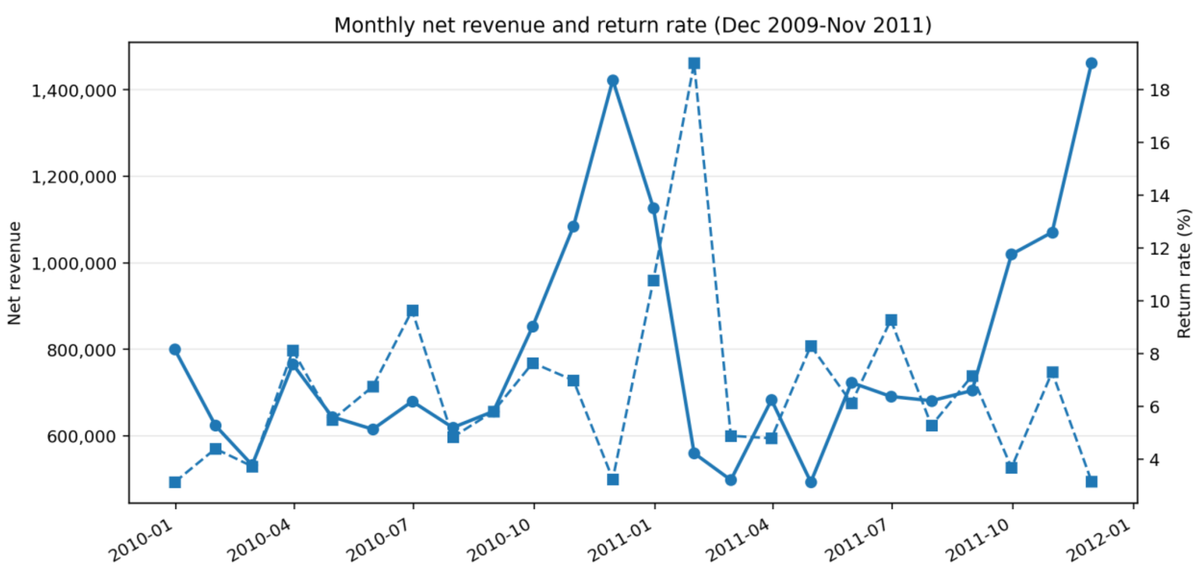
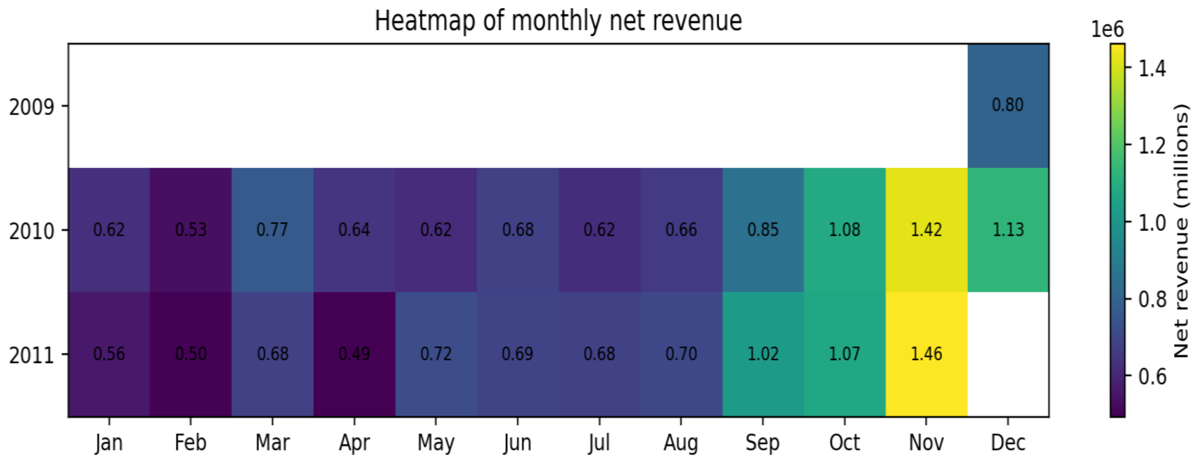


Figure 1 shows two features that are especially important for SME reporting design. First, revenue movement is not smooth; it exhibits distinct surges and contractions, implying that managers need recurring rather than occasional financial review. Second, return rates do not move mechanically with revenue. Some months combine strong revenue with elevated return pressure, meaning that revenue growth can mask underlying quality problems unless the dashboard presents both indicators side by side.

© AUG 2026 | IRE Journals | Volume 10 Issue 2 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I2-1722411

Figure 2. Heatmap of monthly net revenue.



The heatmap in Figure 2 makes seasonality visually explicit. Revenue intensity strengthens markedly from September to November in both full years, with November emerging as the strongest month in the sample. In practical SME reporting terms, such seasonality should feed directly into procurement, staffing, cash planning, and budget phasing. A reporting pack that presents only year-to-date totals would obscure this operational reality.

4.2 Variance analytics, dashboard logic, and concentration risk

A decision-ready accounting dashboard should not only report levels; it should also expose deviation from expected patterns. Table 3 compares actual net revenue for the final six complete months against a trailing three-month baseline. The results show clear positive breakouts in September, October, and November 2011, when actual net revenue materially exceeded the trailing baseline. In contrast, June through August 2011 were comparatively softer. For an SME finance team, such simple variance analysis is often sufficient to trigger deeper operational questions: Was the change driven by demand, pricing, customer mix, returns, or execution issues?

Table 3. Six-month variance review against a trailing three-month baseline.

Month	Trailing 3-month baseline	Actual net revenue	Variance (%)	Return rate (%)	Orders
Jun-11	633,269.24	691,123.12	9.14	9.27	1533
Jul-11	635,887.92	681,300.11	7.14	5.27	1475
Aug-11	698,585.58	704,804.63	0.89	7.16	1361
Sep-11	692,409.29	1,019,687.62	47.27	3.67	1837
Oct-11	801,930.79	1,070,704.67	33.52	7.30	2040
Nov-11	931,732.31	1,461,756.25	56.89	3.16	2769

Correlation analysis reinforces the logic of indicator selection. Orders and active customers show strong positive associations with net revenue ($r = 0.920$ and $r = 0.886$, respectively), while return rate is negatively associated with net revenue ($r = -0.232$). Average order value and revenue per customer provide a second explanatory layer, capturing mix and yield effects rather than pure activity volume.

Table 4. Correlation between selected KPIs and net revenue.

KPI	Correlation with net revenue
Orders	0.92
Active customers	0.89
Average order value	0.43
Return rate (%)	-0.23
Revenue per customer	0.53

© AUG 2026 | IRE Journals | Volume 10 Issue 2 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I2-1722411

Figure 3. Dashboard heatmap of standardized monthly KPIs.

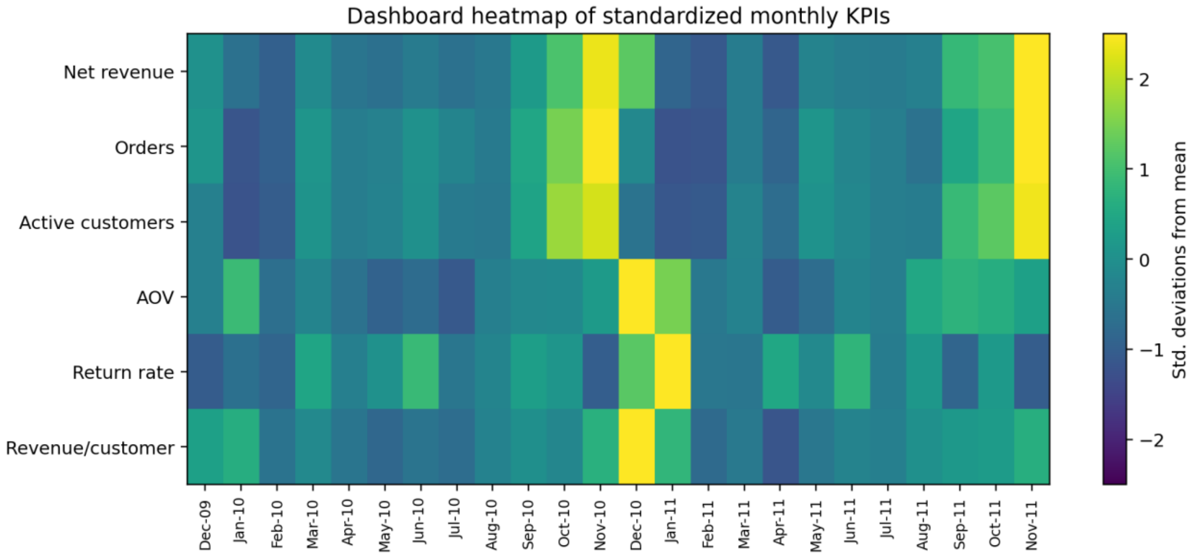
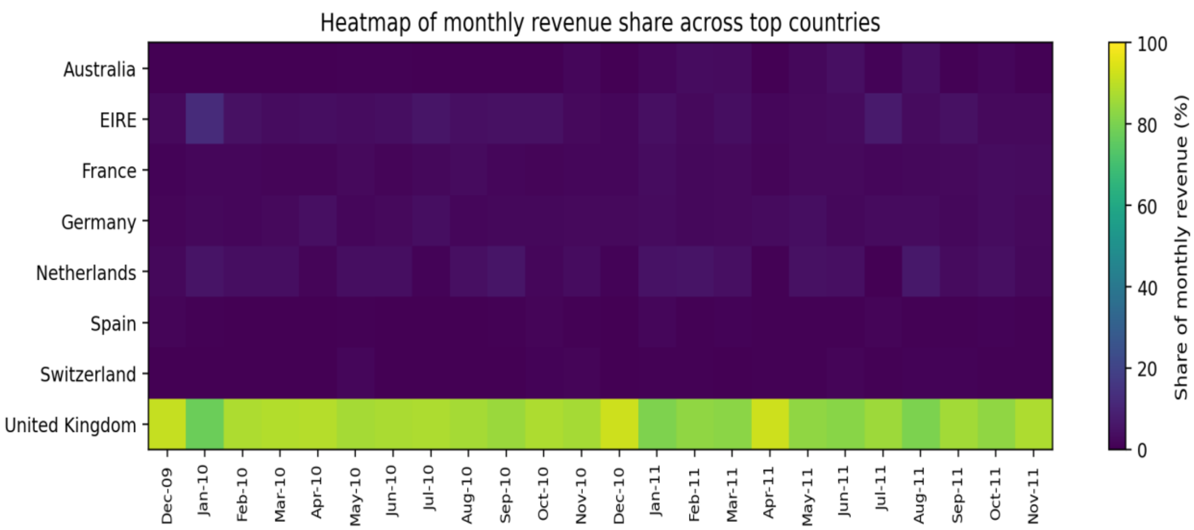


Figure 3 illustrates why heatmaps are useful in management reporting. They compress a wide KPI set into one visual surface and make outlier months immediately visible. November 2010, for example, emerges as a strong month across multiple dashboard dimensions, while January 2011 stands out for elevated return-rate pressure. For SMEs with limited finance headcount, such condensed visual diagnostics reduce the cognitive load of month-end review.

Figure 4. Heatmap of monthly revenue share across top countries.



Concentration reporting is another critical control. The sample is heavily concentrated, with the leading country accounting for 82.98% of known-customer revenue and the top five countries accounting for 94.03%. Figure 4 therefore serves as a proxy for the type of customer, product, or market concentration heatmap that SMEs should maintain. Concentration risk matters not only for sales strategy but also for cash forecasting, because liquidity vulnerability rises when a narrow revenue base dominates the income stream.

© AUG 2026 | IRE Journals | Volume 10 Issue 2 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I2-1722411

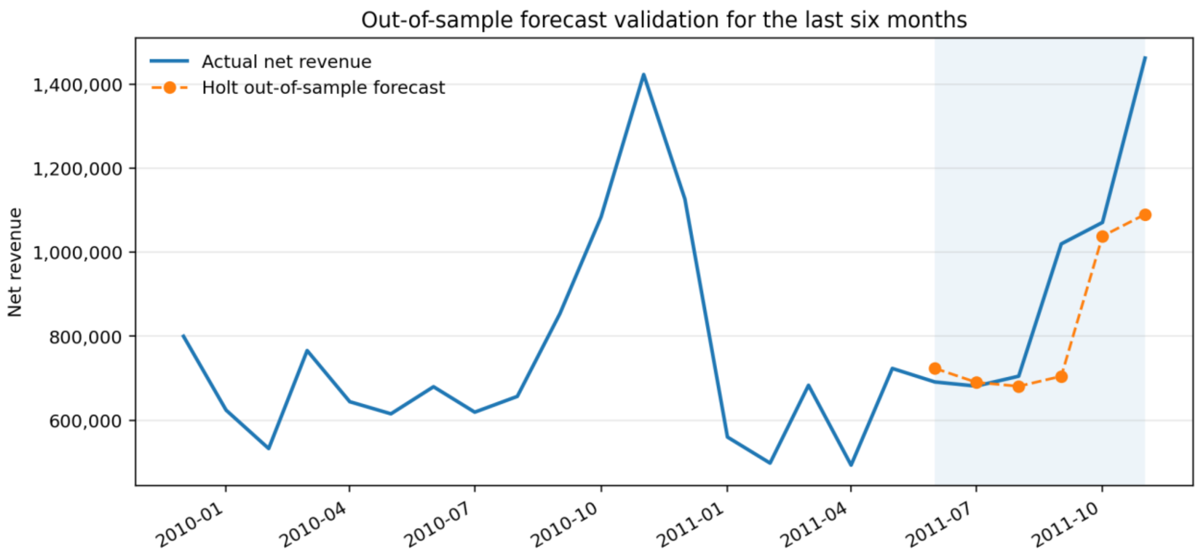
4.3 Forecast validation

A recurrent challenge in SMEs is the assumption that forecasting requires overly sophisticated tools. The present results suggest otherwise. When the last six months of the sample were treated as an out-of-sample validation window, the Holt linear model generated the lowest forecast error across all three evaluation metrics. This indicates that a parsimonious trend-based model can materially improve planning quality in settings where data history is moderate and finance capacity is constrained.

Table 5. Out-of-sample forecast performance for monthly net revenue.

Forecast model	MAE	RMSE	MAPE (%)
Holt linear	130,798.07	200,070.13	11.47
Naive	137,081.59	206,705.04	11.97
3-month moving average	205,926.88	278,604.83	18.23

Figure 5. Out-of-sample forecast validation for the last six months.



The Holt model achieved a MAPE of 11.47%, compared with 11.97% for the naïve model and 18.23% for the three-month moving-average baseline. This does not imply that more complex models are unnecessary; rather, it shows that SMEs can obtain planning value from relatively simple forecasting discipline. The critical managerial requirement is not model complexity per se, but a repeatable process for comparing forecasts with actuals, documenting error, and revising assumptions in response.

V. A PRACTICAL FRAMEWORK FOR DECISION-READY ACCOUNTING ANALYTICS

Drawing on the literature and the empirical results, this paper proposes a five-layer framework for

decision-ready accounting analytics in SMEs. The framework is intentionally pragmatic. It assumes that many SMEs operate without large data-science teams and therefore need a design that can be implemented through mainstream accounting software, spreadsheet models, dashboard tools, and disciplined monthly review routines.

© AUG 2026 | IRE Journals | Volume 10 Issue 2 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I2-1722411

Table 6. Practical framework for data-driven SME financial reporting and forecasting.

Framework layer	Core analytics	Control emphasis	Management output
1. Transaction capture and reconciliation	Daily sales feeds, invoice matching, cancellation tagging, exception logs	Completeness checks, duplicate detection, invoice-to-cash review, unresolved exception list	Daily exceptions report, weekly close checklist, month-end reconciliation pack
2. Diagnostic reporting and control analytics	Gross sales, net sales, return rates, order counts, active customers, customer/geography concentration	Threshold alerts for adverse variance, abnormal returns, sales concentration and missing records	Decision-ready dashboard for owner-managers and finance leads
3. Liquidity and working-capital visibility	Collections ageing, short-term obligations, cash buffer days, inventory turn, payables cadence	Weekly liquidity stress test, overdue-customer drill-down, scenario flags	13-week cash view and weekly liquidity action list
4. Rolling forecasting and variance engine	Trailing averages, trend models, simple exponential smoothing or Holt-based forecasts, budget-to-actual analysis	Model-error tracking, materiality thresholds, variance commentary templates	Rolling 3-month forecast and monthly budget review pack
5. Governance and decision cadence	Assigned metric owners, close calendar, action log, management meeting pack	Escalation rules, documented assumptions, audit trail of decisions and follow-up	Finance governance rhythm linking data, interpretation and action

The first layer transaction capture and reconciliation anchors reporting credibility. If source transactions are not complete, matched, and exception-checked, subsequent analysis is unreliable. The second layer diagnostic reporting and control analytics translates raw transactions into management indicators such as net revenue, returns, order volume, customer activity, and concentration. The third layer liquidity and working-capital visibility extends the framework beyond revenue recognition into cash survival logic through cash buffers, ageing, payables cadence, and short-term stress tests. The fourth layer rolling forecasting and variance analytics converts history into forward-looking control. The final layer governance and decision cadence ensures that analytics produce action, not merely reports.

In practice, the framework supports a monthly close cycle in which reconciliations produce a clean reporting base, dashboards highlight areas of concern, rolling forecasts update the next decision horizon, and management meetings document corrective or growth actions. This integrated cycle is where accounting analytics becomes strategically useful.

VI. DISCUSSION

The findings align with the broader literature in three ways. First, they confirm that reporting quality in SMEs depends heavily on disciplined adoption of management-accounting routines rather than on data volume alone (Ylä-Kujala et al., 2023). Second, they reinforce the view that analytics capability improves the decision value of accounting information (Franke and Hiebl, 2023). Third, they show that practical digital architectures cloud platforms, dashboards, and simple forecast engines can materially improve interpretability and actionability without requiring advanced infrastructure (Sastararuji et al., 2022; Gonçalves et al., 2023).

The empirical illustration also extends recent practical contributions in the SME literature. Ayankoya et al. (2025) emphasise financial optimisation and resilience, while Nhemachena et al. (2026) highlight budget control, receivables visibility, and cash-flow transparency. The present study complements those contributions by explicitly integrating reconciliations, dashboard logic, variance review, and forecast validation into a single operating model.

The results also connect with the distress-prediction literature. Ciampi et al. (2021) and Wang and Guedes (2025) show that financial indicators remain powerful signals in assessing SME vulnerability. The present framework places such signals inside routine management reporting rather than waiting for external credit evaluation. This is especially useful for owner-managed firms, where strategic responses often depend on early internal visibility rather than formal lender diagnostics.

From a governance perspective, the study supports the view that exception detection and control discipline remain critical. Netshifhefhe et al. (2024) argue that stronger control-oriented inquiry improves reporting integrity. In SME settings, that principle can be operationalised through reconciled transaction flows, documented exception logs, concentration reviews, and threshold-triggered management commentary.

VII. MANAGERIAL IMPLICATIONS

For SME owner-managers, the central implication is that decision quality improves when reporting moves from backward-looking compliance packs to forward-looking control systems. A practical starting point is to formalise five metrics at monthly close: net revenue, return rate, order volume, active customers, and short-term cash outlook.

For accountants and finance teams, the study suggests that smaller firms can achieve meaningful analytical gains with a modest tool stack: accounting software, structured exports, a validated KPI model, and a dashboard layer with clearly defined materiality thresholds. The gains come from routine and design, not only technology.

For lenders, advisors, and investors working with SMEs, the findings reinforce the value of management reporting quality as a signal of organisational maturity. Firms that can reconcile data, interpret operational drivers, and maintain rolling forecasts are better positioned to manage volatility, defend margins, and communicate performance credibly.

VIII. CONCLUSION

This paper developed and empirically illustrated a practical framework for data-driven financial reporting and forecasting in SMEs. Using a large public transaction dataset, the study showed that decision-ready reporting requires more than financial statement preparation: it requires reconciled transaction logic, diagnostic KPIs, variance analysis, concentration monitoring, and short-horizon forecast discipline. The results identified strong seasonality, material variation in return rates, and a forecasting structure in which a simple Holt model outperformed naïve and moving-average benchmarks. More importantly, the study translated those results into a five-layer operating framework that smaller firms can adapt to strengthen visibility, liquidity awareness, and managerial response. Future research could extend this framework using full ledger, receivables, payables, and cash data from live SME environments to test its effects on close speed, forecast accuracy, and financial resilience more directly.

REFERENCES

[1] Ayankoya, M.B., Omotoso, S.S., Ogunlana, A.A. et al. (2025) 'Data Driven Financial Optimization for Small and Medium Enterprises (SMEs): A Framework to Improve Efficiency and Resilience in U.S. Local Economies', International Journal of Management and Organizational Research, 4(4), pp. 90–97. doi: 10.54660/IJMOR.2025.4.4.90-97.

[2] Chen, D. (2012) Online Retail II [Dataset]. UCI Machine Learning Repository. doi: 10.24432/C5CG6D.

[3] Ciampi, F., Giannozzi, A., Marzi, G. and Altman, E.I. (2021) 'Rethinking SME default prediction: a systematic literature review and future perspectives', Scientometrics, 126, pp. 2141–2188. doi: 10.1007/s11192-020-03856-0.

[4] Franke, F. and Hiebl, M.R.W. (2023) 'Big data and decision quality: the role of management accountants' data analytics skills', International Journal of Accounting

and Information Management, 31(1), pp. 93–127. doi: 10.1108/IJAIM-12-2021-0246.

[5] Gonçalves, C.T., Gonçalves, M.J.A. and Campante, M.I. (2023) 'Developing Integrated Performance Dashboards Visualisations Using Power BI as a Platform', Information, 14(11), 614. doi: 10.3390/info14110614.

[6] Jenčová, S., Vašaničová, P., Košíková, M. and Miškufová, M. (2025) 'A Time Series Approach to Forecasting Financial Indicators in the Wholesale and Retail Trade', World, 6(1), article 5. doi: 10.3390/world6010005.

[7] Kaggle (n.d.) Online Retail II UCI. Available at: https://www.kaggle.com/datasets/mashlyn/online-retail-ii-uci (Accessed: 21 June 2026).

[8] Netshifhefhe, K., Netshifhefhe, M.V., Mupa, M.N. and Murapa, K.A. (2024) 'The Role of Forensic Audits in Strengthening Corporate Governance and Mitigating Compliance Risks', Iconic Research and Engineering Journals, 8(4), pp. 427–445.

[9] Nhemachena, T.L., Shambare, A.M., Kufandada, D., Chingezi, E., Taanisa, T., Yelduora, P.G., Chawatama, B. and Mupa, M.N. (2026) 'Data-driven budget control, cash-flow visibility, and receivables optimization for U.S. small businesses: A practical accounting-analytics framework', World Journal of Advanced Research and Reviews, 30(1). doi: 10.30574/wjarr.2026.30.1.1164.

[10] OECD (2024) Financing SMEs and Entrepreneurs 2024: An OECD Scoreboard. Paris: OECD Publishing. doi: 10.1787/fa521246-en.

[11] Sastararuji, D., Hoonsopon, D., Pitchayadol, P. and Chiwamit, P. (2022) 'Cloud accounting adoption in Thai SMEs amid the COVID-19 pandemic: an explanatory case study', Journal of Innovation and Entrepreneurship, 11, 43. doi: 10.1186/s13731-022-00234-3.

[12] SBA Office of Advocacy (2026) Frequently Asked Questions About Small Business 2026. Washington, DC: U.S. Small Business Administration.

[13] Wang, W. and Guedes, M.J. (2025) 'Firm failure prediction for small and medium-sized enterprises and new ventures', Review of Managerial Science, 19(7). doi: 10.1007/s11846-024-00742-4.

[14] Ylä-Kujala, A., Kouhia-Kuusisto, K., Ikäheimonen, T., Laine, T. and Kärri, T. (2023) 'Management accounting adoption in small businesses: interfaces with challenges and performance', Journal of Accounting & Organizational Change, 19(6), pp. 46–69. doi: 10.1108/JAOC-07-2022-0100.