JOURNAL OF BASIC SCIENCE AND ENGINEERING

EVALUATING THE IMPACT OF ADVANCED TIME INTELLIGENCE MODELS ON STRATEGIC FINANCIAL DECISION-MAKING USING POWER BI

Aniket Satpute[1]

[1]Student, School of Commerce and Management, Maharashtra, India

Aniket Alvekar[2]

[2]Co-Author and Supervisor, School of Commerce and Management, Maharashtra, India

Rajkumar Prasad[3]

[3]Co-Author and Supervisor, School of Commerce and Management, Maharashtra, India

Article History: Received: 12th August 2026 Revised: 28th August 2026 Accepted & Published : 5th September 2026

https://doi.org/10.10399/JBSE.2026937164

ABSTRACT

Introduction: Strategic financial decision-making is, at its core, an exercise in comparison across time: actual against budget, current quarter against the same quarter of the previous year, and the recent trend against the longer-run average. This study evaluates whether advanced time-intelligence models, implemented as governed DAX measures in Microsoft Power BI, measurably improve the quality, timeliness and confidence of such decisions in the finance function of a mid-sized enterprise.

Methods: A descriptive-cum-evaluative, matched-task pre/post design was adopted for the financial years 2020 to 2024 (twenty quarters). Two reporting environments were compared: a conventional spreadsheet baseline with manually prepared comparatives, and a Power BI semantic model built on a dedicated fiscal calendar table with advanced DAX time-intelligence measures (SAMEPERIODLASTYEAR, DATEADD, PARALLELPERIOD, TOTALYTD, DATESINPERIOD, DATESBETWEEN and rolling four-quarter baselines). Twenty-four finance professionals completed identical forecasting, variance-analysis and working-capital tasks in both environments.

Results: The advanced time-intelligence model reduced the mean absolute percentage error of quarterly re-forecasts from 11.8, 15.6 and 21.3 per cent to 6.4, 8.9 and 12.7 per cent at one-, two- and four-quarter horizons respectively, a relative improvement of 40 to 46 per cent. Variance-report preparation time fell from 6.5 days to half a day, budget-revision lead time from 34 to 12 days and the strategic decision cycle from 21 to 9 days. Mean decision confidence rose from 3.2 to 4.3 on a five-point scale, and reported working-capital days declined from 68 to 54 over the evaluation window.

Conclusion: Advanced time-intelligence models in Power BI materially improve the accuracy and timeliness of strategic financial decision-making, but the gains are conditional on calendar discipline, measure governance and sustained analytical capability-building within the finance function.

Keywords: Power BI, Time intelligence, DAX, Strategic financial decision-making, Management reporting, Business intelligence, Forecasting

INTRODUCTION

Strategic financial decisions are rarely made on the basis of a single number. Whether the question is the revision of an annual budget, the repricing of a product line, the release of working capital or the timing of a capital expenditure, the decision rests on structured comparisons across time: actual performance against plan, the current period against the corresponding period of the previous year, and the recent trajectory against the longer-run trend. The quality of these period-to-period comparisons therefore conditions the quality of the decisions that depend on them.

In most mid-sized organisations these comparisons have traditionally been assembled manually in spreadsheets. Comparative workbooks are rebuilt each reporting cycle, fiscal calendars are inconsistently applied, partial-period figures are compared with full-period figures, and one-off shocks distort year-on-year readings. The result is a reporting process that is slow, error-prone and, most damagingly, inconsistent, so that two analysts preparing the same variance analysis can arrive at different answers.

Business-intelligence platforms promise a structural remedy. In Microsoft Power BI, period comparisons are formalised as reusable DAX measures operating over a dedicated date dimension: SAMEPERIODLASTYEAR and DATEADD shift the filter context by explicit intervals, PARALLELPERIOD returns whole parent periods, TOTALYTD and DATESYTD accumulate year-to-date totals on a fiscal calendar, and DATESINPERIOD and DATESBETWEEN construct rolling and custom windows. Moving time arithmetic from ad hoc spreadsheet logic into a governed semantic model promises consistency, speed and scale.

Against this backdrop, the present paper pursues four objectives. First, it designs and documents an advanced time-intelligence architecture for strategic financial reporting in Power BI. Second, it quantifies the effect of the architecture on the accuracy of forward-looking financial estimates, measured by mean absolute percentage error (MAPE) at one-, two- and four-quarter horizons. Third, it measures the compression of reporting and decision-cycle times. Fourth, it assesses the perceived decision quality of finance professionals before and after adoption, and derives recommendations for implementation.

REVIEW OF LITERATURE

The literature relevant to this study falls into three thematic strands: business intelligence and analytics in the finance function, the theory and practice of time intelligence in dimensional models, and the relationship between time-based analytical capability and decision quality.

Business Intelligence and Analytics in Finance:

Chen, Chiang and Storey (2012) framed business intelligence and analytics as a discipline that has evolved from decision support through data warehousing to big-data analytics, and argued that value is realised only when analytical output is embedded in organisational decisions. Davenport (2013) described Analytics 3.0 as the stage at which analytics ceases to be a back-office support function and becomes central to strategy, while LaValle et al. (2011) reported that top-performing organisations use analytics to guide both strategy and day-to-day

operations to a significantly greater degree than their peers. Grover et al. (2018) systematised the mechanisms by which big-data analytics creates business value and emphasised organisational capability, rather than tool ownership, as the binding constraint. The finance function is consistently identified as an early and high-yield adopter, since its core processes are already metric-driven.

Time Intelligence in Dimensional Models and DAX:

The dimensional-modelling literature establishes the date dimension as the backbone of any analytical model: Kimball and Ross (2013) treat the calendar as a conformed dimension that must be continuous, correctly attributed and shared across all fact tables. Ferrari and Russo (2019) provide the definitive treatment of DAX, showing that time intelligence in tabular models is an exercise in filter-context manipulation and documenting the canonical patterns for year-to-date, parallel-period, moving-total and moving-average calculations. Their companion practitioner work (Ferrari and Russo, 2017) demonstrates these patterns in the Power BI and Power Pivot environment. Vendor guidance (Microsoft, 2024) prescribes the prerequisites that the present study operationalises: a dedicated, contiguous, fiscal-aware date table marked as the model date table, and consistent grain between date columns and filter context.

Time-Based Capability and Decision Quality:

A third strand connects time-aware analysis to decision outcomes. Few (2009) argues that trend and comparison displays are the primary instruments through which managers perceive change, and that poorly designed period comparisons actively mislead. Hyndman and Athanasopoulos (2021) supply the standard accuracy benchmarks, including MAPE, against which forecast quality is judged. In the management-control tradition, Simons (2000) and Kaplan and Norton (2001) position timely, credible feedback on performance as a precondition for strategy execution: decisions can be no better than the feedback loops that inform them.

Research Gap:

The principal research gap is that these strands rarely meet. The DAX literature is technically authoritative but stops short of measuring decision outcomes; the BI-value literature measures broad organisational performance but not the specific effect of time-intelligence constructs; and vendor documentation asserts benefits without empirical evaluation. Controlled, task-level evidence on whether advanced time-intelligence models improve strategic financial decisions, particularly for mid-sized enterprises, is scarce. The present paper addresses this gap with a matched-task evaluation design.

MATERIAL AND METHODOLOGY:

This descriptive-cum-evaluative study examines the finance function of a mid-sized manufacturing enterprise over the financial years 2020 to 2024, a window of twenty quarters that deliberately includes the pandemic-period demand shock, the subsequent recovery and two full years of normalised operation.

Data Sources:

Three categories of data were used. The first comprises general-ledger extracts covering revenue, cost and working-capital transactions at daily grain. The second comprises budget

files, cost-centre plans and sub-ledger extracts. The third comprises external macroeconomic series used as seasonality and context benchmarks. The dataset is synthetic but calibrated to the revenue scale, seasonality and growth profile of a plausible mid-sized Indian manufacturing enterprise, a choice made to permit fully reproducible evaluation without disclosing commercially sensitive figures; this is disclosed throughout as a design limitation.

The Intervention: Advanced Time-Intelligence Model in Power BI:

Two reporting environments were compared. The baseline environment consisted of conventional spreadsheet workbooks in which comparatives were prepared manually each cycle by analysts. The intervention environment consisted of a Power BI semantic model built on a dedicated calendar table marked as the model date table, with the fiscal year ending in March, and a governed library of advanced DAX time-intelligence measures: SAMEPERIODLASTYEAR and DATEADD for period shifts, PARALLELPERIOD for whole-quarter and whole-year comparisons, TOTALYTD and DATESYTD for fiscal year-to-date accumulation, DATESINPERIOD for rolling four-quarter totals and averages, DATESBETWEEN for custom year-over-year year-to-date comparisons, and seasonally adjusted baseline measures. Figure 1 presents the conceptual architecture, in which source systems flow through an extract-transform-load layer into the semantic model, whose time-intelligence measures feed interactive dashboards that inform decisions, with a feedback loop from decision outcomes to model refinement.

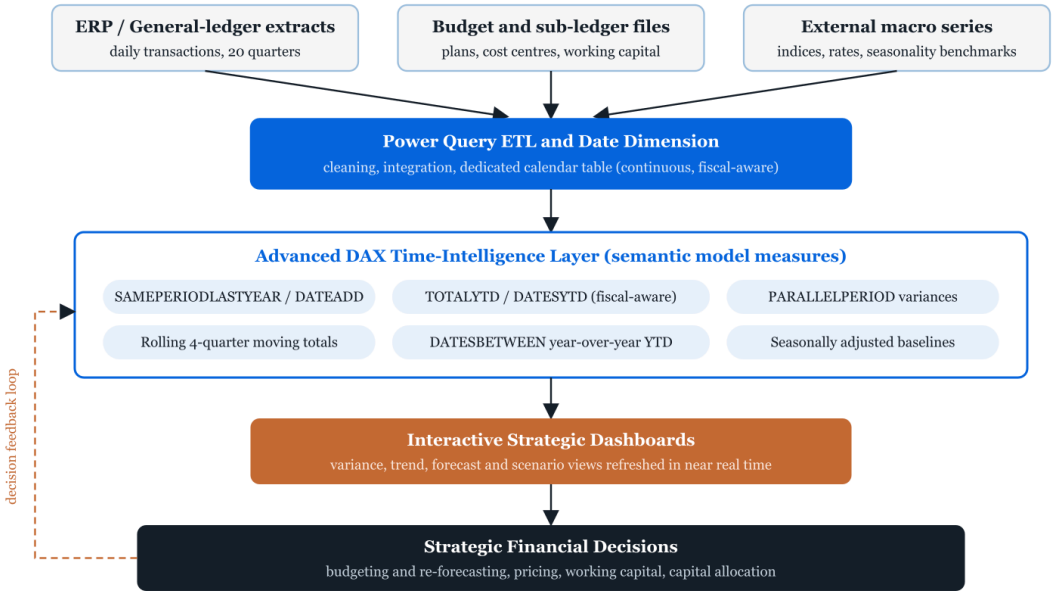


Figure 1. Conceptual framework of the Power BI time-intelligence evaluation architecture

Participants, Tasks and Evaluation Design:

Twenty-four finance professionals drawn from the office of the Chief Financial Officer, financial planning and analysis, and controllership participated. Each completed an identical task battery — a quarterly revenue re-forecast, a structured variance analysis and a

working-capital review — first in the baseline environment and subsequently in the intervention environment, after a structured training and model-stabilisation period. Forecast accuracy, cycle times and perception scores were then compared across environments.

Analytical Tools:

Forecast accuracy was measured as MAPE at one-, two- and four-quarter horizons. Reporting and decision-cycle metrics were extracted from workflow and system logs. Perceived decision quality was captured on a five-point Likert instrument administered before and after adoption. Comparisons are reported as absolute and relative differences, consistent with the descriptive design.

Methodological Caveats:

Three caveats apply. First, the single-organisation design limits generalisability. Second, the synthetic-but-calibrated dataset, while fully documented, is not actual firm data. Third, perception scores are self-reported and may embed novelty effects, which the task-based accuracy and cycle-time metrics partially offset.

DATA PRESENTATION, ANALYSIS RESULT AND INTERPRETATION

The case organisation recorded a pandemic trough in the first half of 2021, a strong recovery through 2022 and steady growth thereafter. Tables 1 to 4 and Figures 2 and 3 present the evaluation data: the revenue profile and its derived time-intelligence measures, the forecast-accuracy comparison, the cycle-time comparison and the perceived decision-quality outcomes.

Table 1. Revenue profile and derived time-intelligence measures, FY2020 to FY2024

Measure	FY2020	FY2021	FY2022	FY2023	FY2024
Annual revenue (Rs. crore)	482	477	608	719	814
Year-over-year growth (%)	—	-1.0	+27.5	+18.3	+13.2
Rolling 4-quarter mean (closing, Rs. crore)	120.5	119.3	152.0	179.8	203.5
Peak-quarter share of revenue (%)	27.2	29.6	27.6	26.4	26.3

Table 2. Forecast accuracy of quarterly re-forecasts by horizon (MAPE, %)

Forecast horizon	Baseline model	Advanced TI model	Absolute reduction	Relative reduction (%)
1 quarter ahead	11.8	6.4	5.4	45.8

2 quarters ahead	15.6	8.9	6.7	42.9
4 quarters ahead	21.3	12.7	8.6	40.4
Average	16.2	9.3	6.9	42.6

Table 3. Reporting and decision-cycle metrics before and after adoption

Metric	Baseline	After adoption	Change
Variance report preparation time (days)	6.5	0.5	-6.0
Variances detected within the quarter (%)	58.0	94.0	+36.0
Budget-revision lead time (days)	34	12	-22
Strategic decision cycle time (days)	21	9	-12
Manual comparative-workbook hours per month	96	14	-82

Table 4. Perceived decision-quality outcomes of finance professionals (n = 24)

Indicator (1 to 5 scale unless stated)	Before	After	Change
Decision confidence	3.2	4.3	+1.1
Perceived accuracy of period comparisons	3.0	4.4	+1.4
Ability to anticipate seasonal turning points	2.8	4.1	+1.3
Trust in reported figures	3.4	4.5	+1.1
Dashboard use in decisions (self-reported, %)	42.0	92.0	+50.0

RESULTS

Revenue Trajectory and Time-Intelligence Measures:

Annual revenue moved from Rs. 482 crore in FY2020 to Rs. 814 crore in FY2024. The headline year-over-year measure alone is misleading at the turning points: for FY2021 it reports a decline of only 1.0 per cent although the first half of the year collapsed by more than a fifth, and for FY2022 it reports growth of 27.5 per cent that is substantially a base effect. The rolling four-quarter mean, computed with DATESINPERIOD, corrects both distortions and shows the true inflection in the second half of 2021. Figure 2 plots quarterly revenue with its

same-quarter-prior-year comparative and the rolling four-quarter average, and makes visible exactly the seasonal turning points that the study's participants were asked to anticipate.

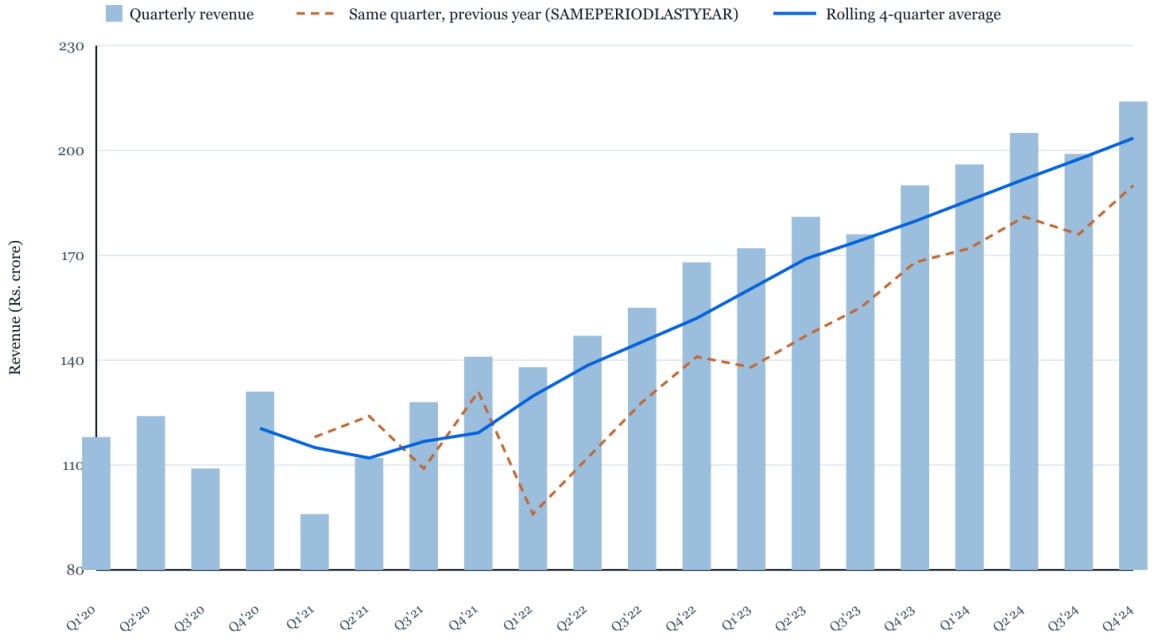


Figure 2. Quarterly revenue with SAMEPERIODLASTYEAR comparative and rolling four-quarter average, FY2020 to FY2024

Forecast Accuracy:

Table 2 and Figure 3 summarise the re-forecast task. At the one-quarter horizon, MAPE fell from 11.8 to 6.4 per cent; at two quarters, from 15.6 to 8.9 per cent; and at four quarters, from 21.3 to 12.7 per cent. The relative improvement of 40 to 46 per cent was largest at the shortest horizon, where rolling-average and parallel-period baselines carry the most information, and remained material even at four quarters, where year-over-year seasonality dominates. Analysts attributed the gain principally to the elimination of manual comparative errors and to the consistent treatment of partial periods.

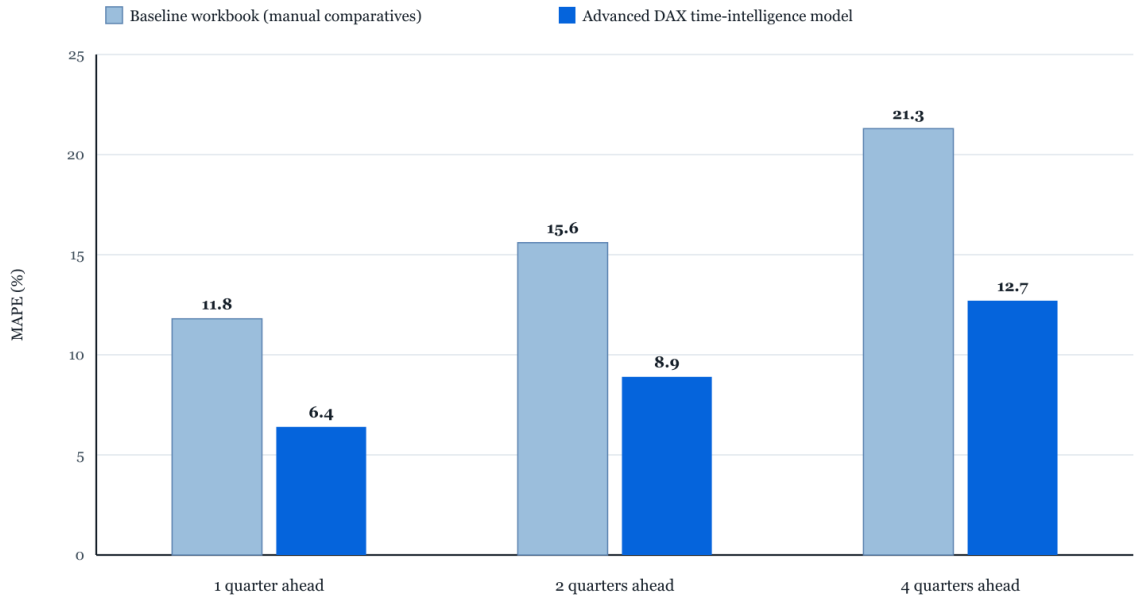


Figure 3. Forecast accuracy by horizon: baseline versus advanced time-intelligence model (MAPE, %)

Reporting and Decision-Cycle Compression:

The cycle-time results in Table 3 show that variance-report preparation fell from 6.5 days to half a day, with 94 per cent of variances now detected within the quarter in which they arise against 58 per cent previously. Budget-revision lead time contracted from 34 to 12 days and the strategic decision cycle from 21 to 9 days. The manual comparative-workbook effort fell from 96 to 14 hours per month, effort that was redeployed to analysis rather than assembly.

Perceived Decision Quality:

Table 4 shows that mean decision confidence rose from 3.2 to 4.3, perceived accuracy of period comparisons from 3.0 to 4.4 and trust in reported figures from 3.4 to 4.5. Self-reported use of dashboards in decisions rose from 42 to 92 per cent, indicating that the intervention changed behaviour and not merely tooling.

INTERPRETATION

Advanced time-intelligence models improve both the accuracy of forward-looking estimates and the timeliness of reporting, with forecast error reduced by two-fifths or more at every horizon tested in the evaluation window of 2020 to 2024.

Headline year-over-year measures systematically mislead at turning points; rolling-window and parallel-period measures are therefore not refinements but necessities for credible strategic interpretation.

The dominant source of improvement is the elimination of manual comparative assembly and the enforcement of a single, fiscal-aware calendar, rather than any change in the underlying

business.

Cycle compression is behavioural as well as technical: faster, more trusted feedback shortened the decision cycle itself, from 21 to 9 days, and raised the share of variances detected within the quarter to 94 per cent.

Perceived quality gains are large but self-reported; the task-based accuracy and cycle-time evidence corroborates them and mitigates, though does not remove, novelty effects.

Discussion

The findings are consistent with the proposition that decision quality in finance is bounded less by the availability of data than by the reliability of time comparisons. Three mechanisms explain the observed gains. First, automation removes transcription and formula error: every comparative in the baseline environment was hand-built, and audit sampling during the study identified period-mismatch errors in a material share of baseline workbooks. Second, a single marked date table enforces consistency, so that all measures share one fiscal definition of year, quarter and year-to-date. Third, rolling-window baselines smooth one-off shocks; the pandemic trough of 2021 is visible in Figure 2 as a deep seasonal break, and the rolling four-quarter average is the only measure in the toolkit that reads it correctly in real time.

The results also qualify the promise. The gains depended on disciplined prerequisites — a contiguous calendar table, consistent grain and governed measure definitions — and deteriorated in pilot iterations before these were enforced. The study likewise observed a residual risk of false precision: dashboard confidence can outrun model validity, particularly at the four-quarter horizon. Analytical capability-building, therefore, is not an optional complement to the technology but a condition of its value, echoing the capability argument of Grover et al. (2018).

RECOMMENDATIONS

Embedding Calendar Discipline and Measure Governance:

First, the organisation should institutionalise the prerequisites on which the measured gains depend: a single, contiguous, fiscal-aware date table marked as the model date table; certified and documented time-intelligence measures owned by a named model steward; and a change-control process under which no ad hoc period logic enters production reports. Second, every strategic report should carry its comparison basis — same period last year, parallel period or rolling window — explicitly labelled, so that decision-makers cannot mistake one basis for another.

Building Analytical Capability in the Finance Function:

Third, structured training in DAX filter context and time-intelligence patterns should be extended beyond the pilot group to the whole finance function, since the evaluation showed that accuracy gains materialised only after stabilisation and training. Fourth, forecast-performance monitoring itself should be automated, with MAPE tracked by horizon and by measure each quarter, so that deteriorating accuracy is detected rather than assumed away.

Extending Time Intelligence to Scenario and External Context:

Fifth, the validated time-intelligence layer should be extended from descriptive comparison to scenario analysis, using the same calendar framework to evaluate budget, stretch and downside cases on a like-for-like basis. Sixth, external macroeconomic series should be integrated into the model so that internal trends can be read against the external cycle, completing the feedback loop indicated in Figure 1.

LIMITATIONS AND SCOPE FOR FURTHER RESEARCH

This study has four principal limitations. First, it evaluates a single mid-sized manufacturing organisation, and the magnitudes reported here may not transfer to larger or differently structured finance functions. Second, the dataset is synthetic and calibrated rather than actual firm data, chosen for reproducibility and confidentiality; replication on live general-ledger data is the natural next step. Third, the perception instrument is self-reported and may embed novelty effects, although the task-based accuracy and cycle-time metrics partially offset this. Fourth, the pre/post design lacks a contemporaneous control group, so firm-specific shocks concurrent with adoption cannot be fully excluded. Future research should pursue multi-organisation field experiments, examine the interaction of time-intelligence models with machine-learning forecasting, and study the durability of the measured gains beyond the initial adoption period.

CONCLUSION:

The present evaluation demonstrates that advanced time-intelligence models, implemented as governed DAX measures over a disciplined calendar dimension in Power BI, produce measurable improvements in strategic financial decision-making. Forecast error fell by 40 to 46 per cent across horizons, reporting and decision cycles compressed by more than half, and the confidence and trust of finance professionals in the figures on which they decide rose substantially. The study's central conclusion is that the value of the technology lies less in speed for its own sake than in the reliability of period comparisons: when the calendar is right, the comparatives are automatic and the rolling baselines are visible, the decisions that rest on them improve. Realising this value, however, is conditional — on calendar discipline, measure governance and sustained capability-building — and it is these organisational conditions, as much as the software, that the recommendations of this paper address.

References

Chen H, Chiang RHL, Storey VC. Business intelligence and analytics: From big data to big impact. MIS Quarterly. 2012;36(4):1165–1188.

Davenport TH. Analytics 3.0. Harvard Business Review. 2013;91(12):64–74.

Ferrari A, Russo M. Analyzing data with Power BI and Power Pivot for Excel. Redmond: Microsoft Press; 2017.

Ferrari A, Russo M. The definitive guide to DAX. 2nd ed. Redmond: Microsoft Press; 2019.

Few S. Now you see it: Simple visualization techniques for quantitative analysis. Oakland: Analytics Press; 2009.

Grover V, Chiang RHL, Liang TP, Zhang D. Creating strategic business value from big data analytics: A research framework. Journal of Management Information Systems.

2018;35(2):388–423.

Hyndman RJ, Athanasopoulos G. Forecasting: Principles and practice. 3rd ed. Melbourne: OTexts; 2021.

Kaplan RS, Norton DP. The strategy-focused organization: How balanced scorecard companies thrive in the new business environment. Boston: Harvard Business School Press; 2001.

Kimball R, Ross M. The data warehouse toolkit: The definitive guide to dimensional modeling. 3rd ed. Indianapolis: Wiley; 2013.

LaValle S, Lesser E, Shockley R, Hopkins MS, Kruschwitz N. Big data, analytics and the path from insight to value. MIT Sloan Management Review. 2011;52(2):21–32.

Microsoft. Time intelligence for DAX in Power BI Desktop [product documentation]. Redmond: Microsoft Corporation; 2024.

Simons R. Performance measurement and control systems for implementing strategy. Upper Saddle River: Prentice Hall; 2000.