Data Analytics for Financial Performance and Risk Analysis: A Finance Analyst's Perspective

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***Abstract*—Financial analysts increasingly work with large volumes of accounting, transaction and operational data. Effective analysis therefore requires more than preparing financial statements: analysts must identify performance trends, explain budget or cost deviations, evaluate control exceptions and communicate decision-relevant insights. This study examines how data analytics can support financial performance and risk analysis from a finance analyst's perspective. A synthetic, non-confidential finance-and-operations dataset containing 288 monthly operating records, 336 financial transactions and a 90-record audit sample was analysed using descriptive statistics, ratio analysis, trend analysis, variance-oriented measures and control-exception analysis. The study finds that the dataset's overall revenue was ₹14.01 million against operating costs of ₹13.89 million, producing a net contribution of ₹0.12 million. Performance varied materially across states and months, illustrating the value of disaggregated analysis rather than relying only on aggregate results. The transaction analysis also identified 73 transactions with missing supporting documentation, representing 21.73% of transactions and 22.55% of transaction value. A small AI-oriented component is discussed as decision support for prioritising unusual or high-risk records, but the paper deliberately keeps professional finance judgement, controls and interpretability at the centre. The findings suggest that finance analysts can create stronger management insight by integrating financial analysis, data validation, visualisation and carefully governed AI-assisted review.**

***Index Terms*—Financial Analytics; Financial Performance; Risk Analysis; Management Reporting; Internal Controls; AI-Assisted Analysis.**

I. INTRODUCTION

Finance functions are increasingly expected to move from reporting what happened to explaining why it happened and what management should do next. Finance analytics uses financial and accounting data to identify patterns, evaluate performance and support decision-making. Gartner describes finance analytics as the use of finance and accounting data to discover patterns that can guide and improve business performance and decisions [1]. This makes data quality, financial interpretation and communication central capabilities for a modern finance analyst.

The role of the finance analyst is especially important in transaction-intensive environments. Accounts payable, expense review, reconciliations, management reporting and financial controls generate repeated observations that can be summarized and analysed. In shared-service environments, standardised processes and common data platforms can increase visibility and process consistency [2]. Empirical research also links finance shared services with profitability and working-capital efficiency [6].

For a finance student, however, analytics should not be treated as a substitute for accounting knowledge. A dashboard may show that costs have risen, but the analyst still needs to determine whether the increase is caused by volume, price, timing, policy, one-off expenditure or an accounting classification issue. Similarly, an automated flag is not evidence of fraud. It is a prompt for review. This study therefore adopts a finance-first view in which data analytics strengthens, rather than replaces, professional judgement and internal controls.

The study is also relevant to the practical skills profile of the author. The uploaded profile identifies PGDM training in Finance and Analytics, financial data analysis, auditing, reporting, Advanced Excel, SQL, Power BI and financial statement analysis [4]. The accompanying GFS job description emphasises accounts payable, reconciliations, expense audits, management reporting, data summarisation, attention to detail and process standardisation [5]. These sources are used only to establish practical relevance; they are not treated as empirical evidence.

II. PROBLEM STATEMENT AND RESEARCH GAP

Many organisations possess financial data but do not always convert it into timely and actionable management insight. Traditional reporting can remain focused on aggregate totals, while decision-makers need to understand trends, drivers, exceptions and financial risks at a more granular level. Existing literature recognises the value of big-data analytics for decision-making and performance, including evidence from Indian firms [2], while financial data analytics literature covers decision support, visualisation, modelling and related applications [3]. Research on finance shared services also demonstrates links between process-level finance performance and broader firm performance [3].

A practical gap remains: finance students and early-career analysts need a simple framework that connects core finance analysis—revenue, cost, margin, variance and control review—with accessible analytics tools. Advanced machine learning is not always necessary. The more immediate requirement is to organise data correctly, calculate meaningful financial indicators, identify exceptions and communicate findings. AI can be introduced at the end of this workflow as a controlled decision-support capability.

III. OBJECTIVES OF THE STUDY

- To examine how data analytics can support financial performance analysis from a finance analyst's perspective.
- To analyse revenue, operating costs and net contribution using trend and comparative analysis.
- To examine transaction-level indicators relevant to financial risk and internal controls.
- To demonstrate how dashboards and structured analytics can improve management reporting.
- To discuss a limited, explainable role for AI-assisted review in prioritising financial exceptions.

IV. RESEARCH QUESTIONS

RQ1: How can data analytics improve the interpretation of financial performance?

RQ2: What financial and control insights can be obtained from transaction-level analysis?

RQ3: How can a finance analyst combine dashboards, financial ratios and exception analysis to support management decisions?

RQ4: What limited role can AI-assisted analysis play without replacing finance judgement and internal controls?

V. LITERATURE REVIEW

Financial data analytics integrates financial information with statistical, computational and visual methods to support analysis and decision-making. Derindere Köseoğlu's edited work positions financial data analytics as a broad field spanning financial data processing, visualisation, modelling and decision-making applications [3]. This supports a finance-led approach in which the analytical technique is selected according to the financial question.

Research on big-data analytics provides evidence that analytics adoption can influence decision-making, forecasting and firm performance. A study using 366 responses from Indian firms reported significant relationships between big-data analytics and decision-making, forecasting and performance [2]. Although the present study does not attempt to establish causal effects, the finding supports the use of analytics as a managerial capability.

Finance shared-service research provides another relevant perspective. Chen, Dai and Na found evidence that finance shared services can affect profitability directly and through working-capital efficiency, illustrating how process-level finance improvements can translate into firm-level outcomes [6]. Liu and Zhao similarly reported that financial shared services were associated with corporate performance and working-capital management efficiency [7]. These studies reinforce the importance of measuring both financial outcomes and the underlying processes that generate them.

Technology can also strengthen financial reporting controls. Ashraf's study of automation in financial reporting found evidence of an association between automation use and fewer internal-control material weaknesses [8]. The implication for a finance analyst is not that automation replaces control ownership, but that well-designed technology can support monitoring and reduce manual weaknesses when governance is maintained.

Overall, the literature suggests three principles adopted in this paper: (1) analytics should begin with a clearly defined business or finance question; (2) financial performance should be connected to process and control indicators; and (3) AI/automation should be treated as an enabling capability with appropriate human oversight.

VI. CONCEPTUAL FRAMEWORK

The proposed framework follows a five-stage finance analytics cycle: Data Quality → Financial Measurement → Performance Interpretation → Risk and Exception Review → Management Decision. AI-assisted analysis is positioned within the fourth stage as an optional prioritisation aid.

TABLE I. FINANCE-FIRST ANALYTICS FRAMEWORK

Stage	Finance analyst activity
1. Data quality	Validate fields, dates, categories and documents
2. Financial measurement	Calculate revenue, cost, contribution, margins and variances
3. Performance interpretation	Compare months, states, categories and trends
4. Risk & exception review	Review missing documents, pending approvals and unusual values
5. Management decision	Recommend action, escalation or further investigation

VII. RESEARCH METHODOLOGY

This study uses an applied descriptive-analytical design. The empirical component is a synthetic research demonstration dataset constructed solely for this research demonstration. It is explicitly not the confidential or historical data of the organisation, the organisation or any other organisation. The workbook documentation states that it is a synthetic finance research dataset and should not be presented as actual company data [10].

The dataset contains 288 monthly centre-level operational observations covering April 2021 to March 2022, 336 financial transactions, and a 90-record audit sample. The analysis uses Excel/Python-style tabular calculations and charting to demonstrate a reproducible finance analytics workflow. The methods include descriptive statistics, aggregation, contribution-margin analysis, comparative state analysis, transaction-category analysis, supporting-document analysis and approval-status analysis.

No causal inference is claimed. The results describe the synthetic dataset only. Consequently, the paper should be interpreted as a proof-of-concept for a finance analyst workflow rather than evidence about a real organisation.

VIII. DATASET AND VARIABLES

TABLE II. DATASET STRUCTURE

Dataset	Records	Main variables	Purpose
Operational data	288	Month, state, centre, students, attendance, revenue, operating cost, contribution	Financial performance and operational comparison
Financial transactions	336	Transaction ID, month, nature, category, counterparty, amount, approval, supporting documents	Transaction and control analysis
Audit sample	90	Transaction ID, category, amount, audit finding, risk level, recommended action	Risk and audit-exception review

Key financial indicators were calculated as follows: Net Contribution = Revenue − Total Operating Cost; Contribution Margin = Net Contribution / Revenue × 100. Transaction control exposure was assessed using the proportion and value of transactions with missing supporting documentation and pending approval status.

IX. RESULTS AND ANALYSIS

A. Overall Financial Performance

Across the 288 operational records, total reported revenue was ₹14,008,277, while total operating cost was ₹13,888,953. The resulting net contribution was ₹119,324, equivalent to an aggregate contribution margin of 0.85%. The relatively narrow difference between revenue and operating cost demonstrates why aggregate revenue alone is insufficient for performance evaluation.

TABLE III. OVERALL FINANCIAL PERFORMANCE

Metric	Value
Total revenue	14,008,277.00
Total operating cost	13,888,953.00
Net contribution	119,324.00
Contribution margin	0.85

Note: The first three values are INR amounts; contribution margin is percentage.

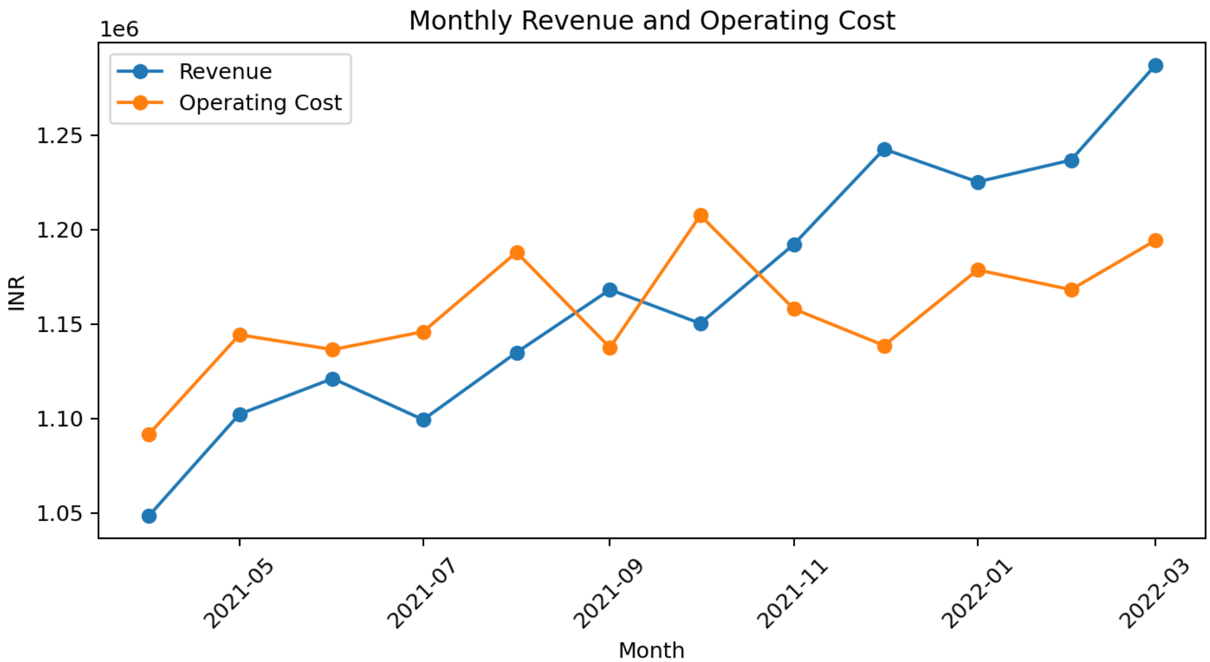

Fig. 1. Monthly revenue and operating cost in the synthetic dataset.

The monthly trend shows that performance improved toward the later part of the period. The weakest monthly contribution occurred in October 2021 at −₹57,223, while the strongest occurred in December 2021 at ₹103,985. The pattern illustrates the value of monthly trend analysis because an annual or full-period aggregate can conceal periods of operating loss and later improvement.

B. State-Level Financial Performance

TABLE IV. STATE-LEVEL FINANCIAL PERFORMANCE

State	Revenue	Operating Cost	Net Contribution	Margin %
Bihar	₹4,581,928	₹3,810,997	₹770,931	16.83%
Uttar Pradesh	₹3,645,395	₹3,497,593	₹147,802	4.05%

State	Revenue	Operating Cost	Net Contribution	Margin %
Madhya Pradesh	₹3,060,992	₹3,326,833	−₹265,841	−8.68%
Jharkhand	₹2,719,962	₹3,253,530	−₹533,568	−19.62%

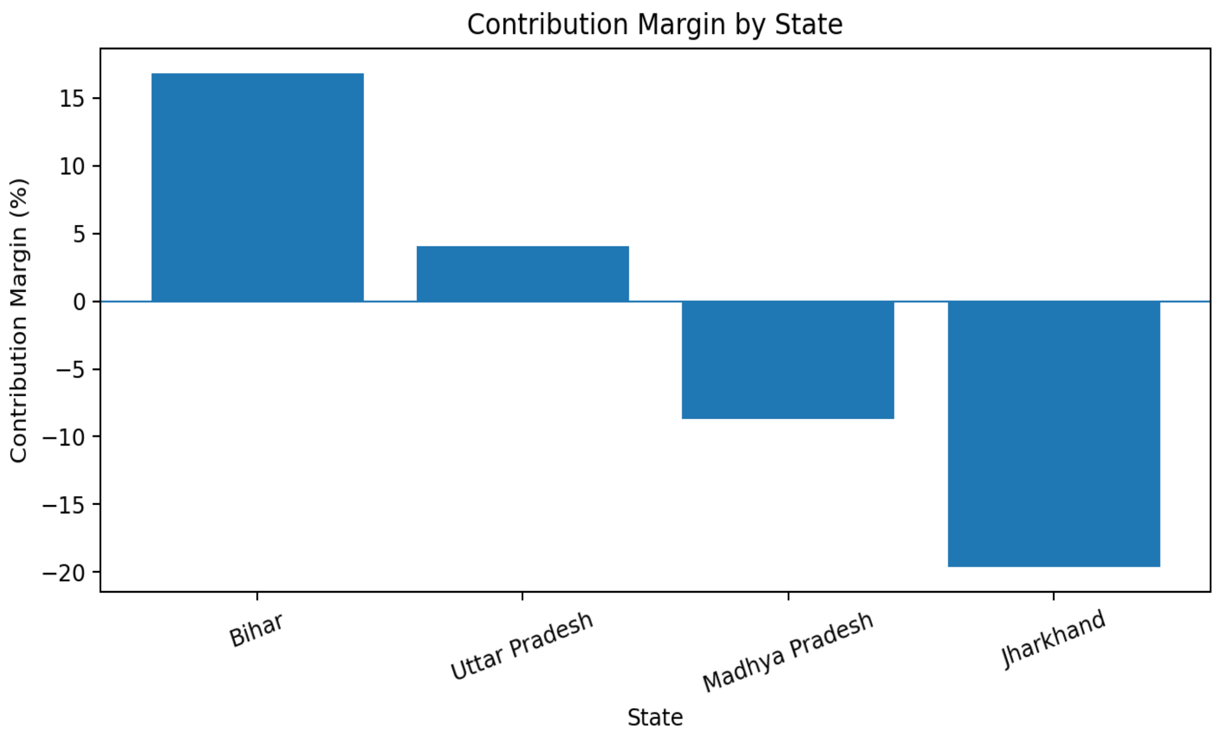

Fig. 2. Contribution margin by state.

Bihar generated the highest revenue in the synthetic dataset (₹4.58 million) and the highest contribution margin (16.83%). Uttar Pradesh also generated a positive margin of 4.05%. Madhya Pradesh and Jharkhand showed negative contribution margins of −8.68% and −19.62%, respectively. This demonstrates an important finance-analyst principle: high revenue does not automatically mean high financial performance. Management should investigate the cost structure and operating drivers behind each region.

C. Transaction Mix and Financial Exposure

TABLE V. MAJOR TRANSACTION CATEGORIES BY VALUE

Nature	**Category**	**Transactions**	**Amount**
Revenue	Institutional/Program Income	51	₹2,033,623
Revenue	Student Fees	38	₹1,575,632
Expense	Center Rent & Utilities	52	₹1,491,723
Expense	Content & Learning Material	47	₹1,472,238
Expense	Office & Admin	42	₹1,203,616
Expense	Teacher Payroll	38	₹1,063,344
Expense	Technology & Connectivity	33	₹1,020,990
Expense	Travel & Field Operations	35	₹997,186

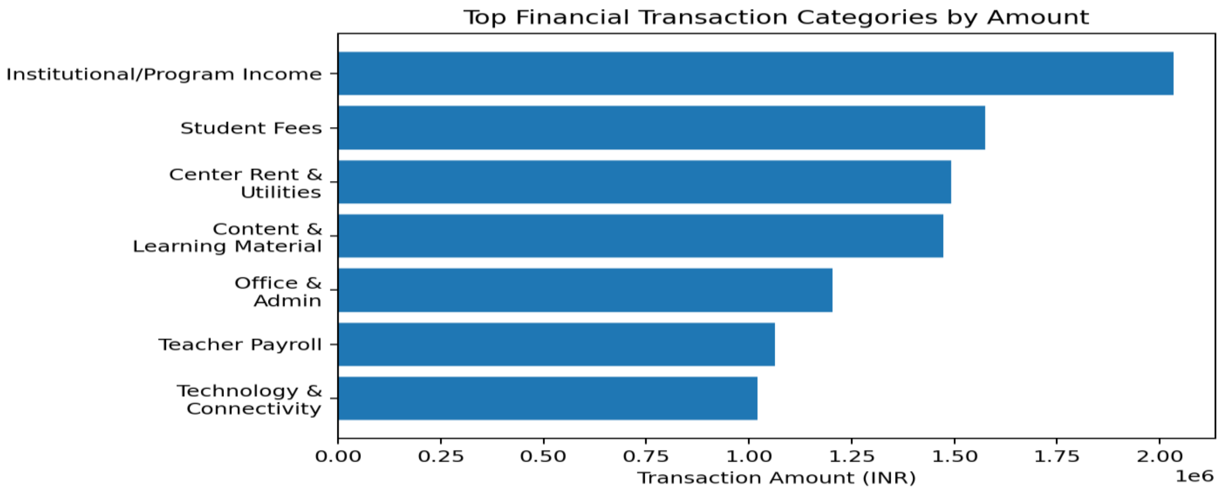

Fig. 3. Highest-value financial transaction categories.

Revenue transactions represented substantial portions of the financial transaction population, while expense categories such as centre rent and utilities, content and learning material, office and administration, teacher payroll, technology and connectivity, and travel/field operations formed important cost groups. Category-level analysis helps the finance analyst move from a total-cost question to a driver-based question: which categories are responsible for the largest financial exposure and should therefore receive management attention?

D. Internal-Control and Risk Analysis

The transaction file contains 336 records with a total value of ₹10.86 million. Of these, 73 transactions had missing supporting documentation. These represented 21.73% of transactions and ₹2,449,975, or 22.56% of transaction value. Pending approvals represented 22.62% of transaction records. These indicators do not prove error or fraud; they identify records that require review under the organisation's control policy.

TABLE VI. SUPPORTING-DOCUMENT STATUS

Supporting_Doc_Status	Transactions	Amount
Complete	263	₹8,408,377
Missing	73	₹2,449,975

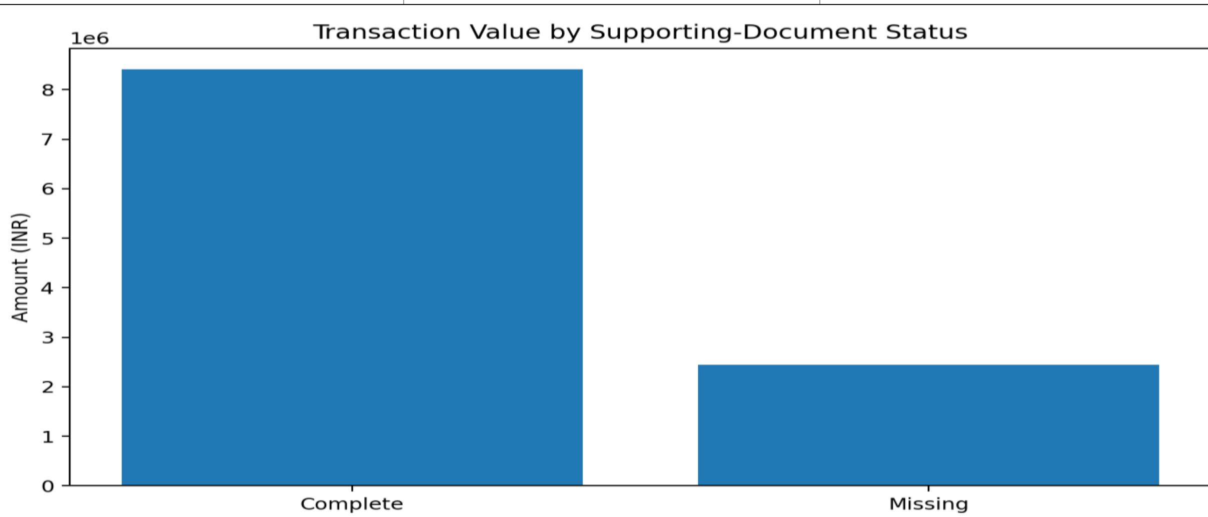

Fig. 4. Transaction value by supporting-document status.

TABLE VII. APPROVAL-STATUS PROFILE

Approval_Status	Transactions	Amount
Approved	200	₹6,478,459
Pending	76	₹2,304,622
Reviewed	60	₹2,075,271

TABLE VIII. AUDIT SAMPLE RISK PROFILE

Risk_Level	Transactions	Amount
Low	57	₹1,897,322
Medium	33	₹1,034,102

The audit sample contained 57 low-risk and 33 medium-risk observations. The absence of a high-risk label in this sample should not be interpreted as proof that no high-risk items exist; it simply describes the supplied audit sample. A finance analyst should combine sample findings with transaction controls, materiality, policy thresholds and professional judgement.

E. Variance and Margin Interpretation

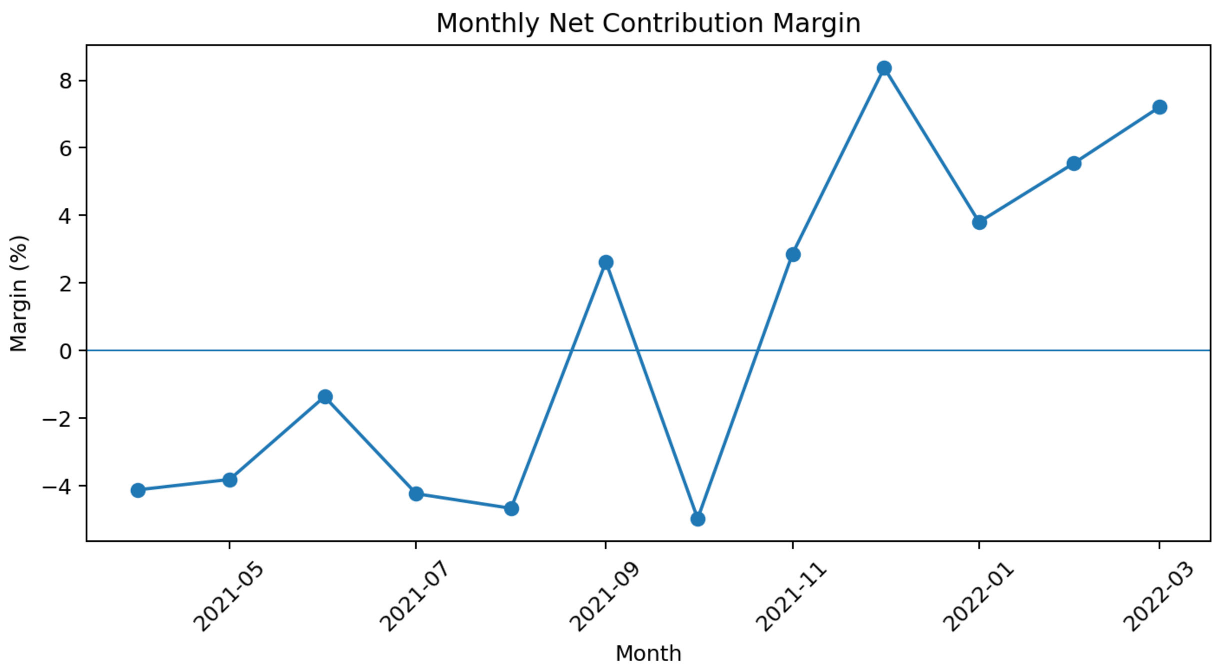

Fig. 5. Monthly net contribution margin.

The contribution-margin trend reinforces the importance of variance analysis. The best month was Dec-2021 with a contribution of ₹103,985 and margin of 8.37%, whereas the weakest month was Oct-2021 with a contribution of ₹-57,223 and margin of -4.97%. Management reporting should therefore pair financial totals with explanations of the underlying drivers.

X. LIMITED ROLE OF AI IN FINANCE ANALYSIS

AI is intentionally treated as a supporting capability rather than the research centre of this paper. A practical finance application is AI-assisted review of large transaction populations. For example, an analyst can define transparent review signals—missing documentation, pending approval, unusually large amount, duplicate-looking patterns or unexpected category behaviour—and use an AI-enabled analytics layer to prioritise records for human review.

In this study, a simple transparent prioritisation score was demonstrated as a proof-of-concept rather than a machine-learning model. Two points were assigned for missing supporting documentation, one point for pending approval and two points for an amount at or above the 95th percentile. This produces an explainable review queue. The score is not a fraud score and should not be used to make automatic accounting or disciplinary decisions.

This approach is consistent with the broader literature showing that automation can support financial reporting and internal-control outcomes [9]. The finance analyst remains responsible for checking source documents, understanding business context, confirming accounting treatment and escalating genuine issues. Thus, the appropriate relationship is AI-assisted analysis plus human financial judgement, not AI replacing the analyst.

TABLE IX. ILLUSTRATIVE HIGH-PRIORITY REVIEW QUEUE (SYNTHETIC DATA)

Transaction	Category	Amount (INR)	Approval	Documents	Priority
TXN-100318	Student Fees	₹61,316	Approved	Missing	4
TXN-100281	Institutional/Program Income	₹60,853	Approved	Missing	4
TXN-100107	Student Fees	₹58,449	Reviewed	Missing	4
TXN-100150	Institutional/Program Income	₹57,003	Reviewed	Missing	4
TXN-100118	Student Fees	₹56,134	Approved	Missing	4
TXN-100135	Student Fees	₹55,743	Approved	Missing	4
TXN-100293	Institutional/Program Income	₹62,569	Pending	Complete	3
TXN-100006	Content & Learning Material	₹49,959	Pending	Missing	3
TXN-100211	Student Fees	₹45,992	Pending	Missing	3
TXN-100299	Travel & Field Operations	₹43,914	Pending	Missing	3

The high-priority table is intentionally transparent: an analyst can see why a transaction entered the queue. Such explainability is more appropriate for finance control environments than a black-box score whose meaning is difficult to interpret.

XI. DISCUSSION

The results demonstrate three practical lessons. First, financial performance must be analysed at more than one level. The overall dataset produced a positive but small net contribution, while monthly and state-level analysis showed substantial variation. A finance analyst who reports only the aggregate figure could miss loss-making periods and regions.

Second, performance analysis and risk analysis should be connected. Missing supporting documents and pending approvals are not merely administrative observations. They can affect the reliability, auditability and timeliness of financial information. A finance dashboard can therefore combine financial KPIs with control KPIs.

Third, analytics creates value when it improves the quality of a management conversation. The output should not be a collection of charts; it should answer questions such as: Why did margin change? Which cost category contributed most? Which region requires attention? Which transactions require evidence? What action should management take?

These findings are consistent with research showing that analytics can support decision-making and performance [6], and that technology-enabled finance processes can influence financial outcomes through improved process performance [3]. The contribution of the present study is practical rather than causal: it demonstrates a finance-student-friendly workflow that connects accounting concepts, analytics and limited AI assistance.

XII. IMPLICATIONS FOR FINANCE ANALYSTS

- Start with the finance question, not the technology. Define the decision, KPI or risk to be analysed before selecting a tool.
- Validate source data before calculating KPIs. Incorrect categories, dates or amounts can create misleading management reports.
- Use variance analysis to explain movement, not simply to report that a number changed.
- Combine financial KPIs with control indicators such as documentation completeness, approval status and reconciliation exceptions.
- Use dashboards to make patterns visible, but retain the underlying transaction-level evidence for auditability.
- Treat AI outputs as review suggestions. Final accounting, compliance and risk decisions require human judgement and documented controls.

XIII. LIMITATIONS

- The empirical dataset is synthetic and therefore cannot establish conclusions about a real company or industry.
- The dataset covers a limited period and a synthetic study model business context.
- The analysis is descriptive; no causal relationships are estimated.
- Working-capital ratios such as receivable days, payable days and cash-conversion cycle could not be calculated because the dataset does not contain the required balance-sheet fields.
- The AI component is deliberately limited to an explainable prioritisation concept and does not establish the accuracy of a machine-learning model.
- Results and tables must not be represented as historical the organisation or the organisation figures.

XIV. FUTURE RESEARCH

Future research can use a real, permissioned finance dataset containing budget, actual, accounts receivable, accounts payable, working capital and reconciliation data. A larger longitudinal sample could support panel analysis of financial performance. Researchers could also test whether AI-assisted exception review reduces review time or increases the proportion of genuine exceptions identified, while maintaining audit trails and human approval.

XV. CONCLUSION

This study demonstrates that finance analytics can strengthen financial performance and risk analysis without requiring the finance analyst to become a machine-learning engineer. Using a synthetic proof-of-concept dataset, the analysis connected revenue, operating cost, contribution margin, regional performance, transaction categories, supporting-document status and approval status. The results show meaningful variation that becomes visible only when finance data are analysed at monthly, regional and transaction levels.

The study's central conclusion is that the strongest finance analytics workflow is finance-first: validate data, calculate meaningful financial measures, analyse variances and trends, identify control exceptions, visualise the results and communicate an actionable recommendation. AI can add value by helping analysts prioritise large volumes of records, but it should remain transparent, governed and subject to professional judgement. For finance students, this combination of accounting knowledge, analytical thinking and responsible technology use represents a practical and employable model of modern financial analysis.

XVI. RESEARCH INTEGRITY AND GENERATIVE AI DISCLOSURE

The empirical dataset used in this paper is a synthetic research demonstration dataset and is explicitly identified as such. No confidential employer data are used. The author should independently verify all calculations, references, originality, institutional details and final formatting before submission. Generative AI tools were used to assist with drafting, language refinement, analytical structuring and document preparation. The human author remains responsible for the research question, interpretation, accuracy, originality, source verification and final manuscript.

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APPENDIX A. KEY DATASET DEFINITIONS

TABLE A-I. KEY VARIABLE DEFINITIONS

Variable	Finance interpretation
Fees_Revenue_INR	Revenue recorded in the practice model
Total_Operating_Cost_INR	Centre plus teacher operating costs
Net_Contribution_INR	Revenue less operating cost
Attendance_Pct	Average monthly attendance indicator
Amount_INR	Transaction monetary value
Approval_Status	Transaction approval stage
Supporting_Doc_Status	Evidence/document completeness status

APPENDIX B. IJIRT SUBMISSION CHECKLIST

- Confirm author name, affiliation and email exactly match the IJIRT submission form.
- Use the current IJIRT DOC/DOCX submission format and verify any sample template requirements.
- Check that the manuscript is original and not simultaneously submitted elsewhere.
- Run an institutional plagiarism/originality check.
- Verify every reference and DOI/URL before submission.
- Verify all numerical tables and charts against the final dataset.
- Keep the synthetic-data disclosure if this dataset remains the empirical basis.
- Disclose GenAI use transparently as required by IJIRT.