

# a₹tha

E - JOURNAL OF FRTL @ IIM CALCUTTA

September 2024. Volume 12. Issue 2



# Unconventional Financial Analytics

Vilas Sateesh

## 1. ABOUT THIS ARTICLE

In today's data driven business world, the term "data analytics" is no longer a buzzword. As per a study conducted by BARC in 2023, data driven culture is one amongst the top 5 emerging trends (BARC, 2023, "Data, BI and Analytics Trend Monitor-2024). Organizations of various multitude have adopted analytics as a key component of their DNA. Of late, analytics often gets coined with machine learning and artificial intelligence concepts to provide real time or near real time insights to various business functions. Out of all the business functions, finance is one of the earliest adopters of analytics in the modern era as early as 1970s, for risk analysis using quantitative models processing a wide range of historical financial and economic data (International Journal of Education and Research, 2013, Financial Theory Evolution). As the scope of analytics gets expanded day by day, so is the case with Finance, ranging from analyzing historical data to prediction of future performance and financial behaviours. Even though this article talks about financial analytics and its common applications, the focus of this article is all about application of analytics in unconventional ways to aid financial management activities.

## 2. INTRODUCTION

Analytics could be defined as the systematic examination of data using data visualization, statistical models and quantitative analysis. The objective of analytics is to identify patterns, relationships, trends and inferences that can make better decisions, solve problems or improve performance. From a business perspective, analytics aids better decision making, optimized business processes, better risk management, drive innovation with the penultimate aim of providing a competitive edge to the business.

Broadly speaking there are four different types of analytics.

1. **Descriptive analytics** – Provides a holistic view of historical data to understand what has happened in the past, e.g. representation of sales performance of the organization across multiple segments, geographies, periods, etc.
2. **Diagnostic analytics** – Building from the descriptive, diagnostic analytics examines the underlying data to analyze why something happened, e.g. why revenues dropped in a particular period. As per a global study conducted by Gartner, it is predicted that by 2027, 90% of descriptive and diagnostic analytics in finance will be fully automated (Gartner, 2024, Garner Finance Predicts – Leadership Vision for 2024 – Top 5 Strategic Priorities for Heads of Financial Planning & Analysis)
3. **Predictive analytics** – On top of analyzing why something happened, predictive analytics embeds statistical models to forecast or predict certain business outcomes, i.e. "what could happen", e.g. predicting the impact of a critical manufacturing component failure on the revenues of the business.
4. **Prescriptive analytics** – Goes one level further in terms of suggesting "what should be done" to achieve desired outcomes or to solve certain problems, e.g. a well-defined predictive maintenance model can suggest based on data, what should be the appropriate maintenance schedule to keep the equipment down time minimal so that the revenue of the business is impacted minimally.

Narrowing down the definition of analytics to Finance, financial analytics is the systematic analysis of financial data to aid financial management. In Finance, analytics could take the form of conventional analytics such as analysis of financial statements or unconventional methods to predict certain financial behaviour, detection of financial red flags, etc.

Regardless of whether it be conventional or unconventional, analytics gives a lot of ammunition to finance in terms of providing strategic and valuable insights to business rather than just providing historical facts and figures. Finance leaders today spend 19% more time on value added activities than typical finance organization did a decade ago (McKinsey & Company, November 2020, Finance 2030: Four Imperatives for the next decade). Modern day finance functions plays a key role in devising organizational strategy, business plans, risk management, etc. and unconventional methods of financial analytics is the driving engine for the same. Before we dwell into the application of unconventional analytics in finance, it is crucial first to understand what conventional financial analytics and its typical applications is. This would better facilitate an understanding of unconventional financial analytics and how it addresses the shortcomings of conventional analytics.

### 3. CONVENTIONAL FINANCIAL ANALYTICS

Conventional financial analytics is the application of traditional methods to perform financial management using traditional financial information. Examples include financial statement analysis to evaluate the performance of an organization, investment decision analysis or feasibility analysis to evaluate the financial viability of an upcoming investment or project, etc.

Even though the term conventional financial analytics may sound traditional, its application cannot be undermined. In fact, in most organizations, conventional financial analytics is the most sought-after application for finance to provide initial insights. Unconventional methods are then added as a further layer to provide certain specialized areas of input.

#### 3.1 Typical application areas of conventional financial analytics (non-exhaustive)

| # | Application area                  | Description  |
|---|-----------------------------------|--|
| 1 | Financial statement analysis      | Involves computation of financial ratios to assess a company's performance, profitability, liquidity position, etc. Typically, these ratios are compared across multiple periods to assess trends or across multiple companies in the same industry sector to assess competitiveness.  |
| 2 | Financial forecasting & budgeting | Typically used for a company's financial planning / forecasting, this involves usage of historical data and certain growth assumptions to plan for company's finances for the upcoming period(s). Various budgeting techniques such as incremental budgeting, driver-based budgeting, incremental budgeting, rolling forecasts, etc. could be deployed here. As per a global study conducted by Gartner, it is predicted that by 2028, 50% of organizations will have replaced time consuming manual forecasting approaches with AI (Gartner, 2024, Garner Finance Predicts – Leadership Vision for 2024 – Top 5 Strategic Priorities for Heads of Financial Planning & Analysis). |
| 3 | Variance analysis                 | Involves comparison of actual costs against budgets or pre-defined standard costs to identify deviations and take corresponding corrective measures. Used for both financial management as well as for cost control purposes.  |
| 4 | Investment analysis               | Used for measuring the financial viability of an investment proposal, be it be a new business or a new project initiative. Involves analyzing key metrics of financial projections such as net present value (NPV), internal rate of return (IRR), payback period, return on investment, etc.  |

|   |                      |  |
|---|----------------------|--|
| 5 | Sensitivity analysis | Used for evaluating how changes in key scenarios or assumptions (e.g. interest rates, inflation rates, etc.) could affect financial projections. |
|---|----------------------|--|

### 3.2 Shortcomings of conventional methods

A key limitation of the conventional methods is that since most of the analysis is performed using historical data and information, the outcome also tends to be more like post-mortem analysis and lacks foresight. Other shortcomings include:

- Prone to errors as the analysis often involves manual analysis.
- Limited scalability and is not well suited for analyzing large and complex data sets.
- Real time analysis is mostly not possible.
- Cannot handle unstructured data or cannot perform analysis by integrating data from multiple data sources.

## 4. UNCONVENTIONAL FINANCIAL ANALYTICS

Unconventional methods try to overcome the limitations of conventional analytics by providing a forward-looking view, by analyzing vast amounts of alternate sources of data and may also have the capability to provide real time analysis. These unconventional methods offer a lot of business benefits that go beyond the remit of financial management. In financial management domain, we could broadly classify these unconventional methods into three broad categories as per the needs they serve to the business. These are:

1. Fraud and error detection
2. Performance prediction
3. Risk management

Most of these methods utilize statistical, quantitative or combination of the two coupled with machine learning techniques data depending upon the specific functional need.

### 4.1 Fraud and error detection

In today's corporate business environment, the terms "fraud" and "error" are no longer strangers, at least within the finance domain. Increasing transaction volumes, advent of ever evolving technology and increasing complexity of the macro and micro economic factors generally make organizations increasingly susceptible to fraud and errors. Based on a recent study conducted by Association of Certified Fraud Examiners covering 1921 cases from 138 countries and territories, fraud caused total loss of USD 3.1 billion (Association of Certified Fraud Examiners, 2024, Occupational Fraud 2024 – A Report to the Nations).

A few common fraud and error detection techniques are explained below. It should be noted that these techniques are not perused by Finance alone, rather are being used by auditors as well in conjunction with forensic accounting.

### Benford's Law

Benford's Law, also known as "law of first digits," is primarily used to determine whether there is an artificial influence either due to fraud or error on the data set. As per this law, in a dataset with big enough sample size and where values correspond to natural numbers, then the probability of occurrence of the first digits should look like the following:

| 1     | 2     | 3     | 4    | 5    | 6    | 7    | 8    | 9    |
|-------|-------|-------|------|------|------|------|------|------|
| 30.1% | 17.6% | 12.5% | 9.7% | 7.9% | 6.7% | 5.8% | 5.1% | 4.6% |

If the overall distribution of the digits does not conform to this pattern within tolerable limits (defined using statistical model "Z" test), then one could infer that there has been some artificial influence of error or fraud and as such the data may not be reliable



where the percentage has significant deviations. Benford's Law also gives predictions on second digit, third digit, combination of first, second and third digits and even round numbers. It should be noted that this law will apply only if the data size is large enough.

This law will not further work if the numbers are controlled to a specific value, or in the case of numbers generated by a random number generator.

Benford's Law is typically used in the finance domain for multiple purposes including audit. An increasing area of application is the expenditure review to detect broken payments to circumvent approval limits. Another area of application is to detect manipulation of sales data either for misappropriation or for portraying false picture to meet targets.

### **Beneish Model**

Based on a study conducted by Association of Certified Fraud Examiners covering 1921 cases from 138 countries and territories, financial statement frauds contributed to 5% of cases and median loss per case was valued at USD 766,000 (Association of Certified Fraud Examiners, 2024, Occupational Fraud 2024 – A Report to the Nations).

Beneish Model, also known as "M-score" (manipulation score) is a statistical model designed to detect financial statement manipulations by companies. The model is based on eight accounting metrics that are believed to be indicators of manipulation. M-score is calculated as:

$$-4.84 + 0.92(\text{Days sales in receivables index}) + 0.528(\text{Gross margin index}) + 0.404(\text{Asset quality index}) + 0.892(\text{Sales growth index}) + 0.115(\text{Depreciation index}) - 0.172(\text{Sales, general \& administrative expenses index}) + 4.679(\text{Total accruals to total assets}) - 0.327(\text{Leverage index})$$

An M-score greater than -2.22 signals a strong possibility of the company being a manipulator of its financial statements. Analysis requires at least 2 years of data to be analyzed even though 4-5 years is advisable.

The model is typically used by financial auditors as well as investment companies who want to evaluate whether there has been any intentional misrepresentation of financial position. It should however be noted that this is not the only method adopted by financial reviewers to conclude about the fairness of financial representation, rather this is one of the methods adopted in conjunction with standard audit techniques.

### **Luhn algorithm**

Also known as "modulus 10" or "mod 10" algorithm is a checksum formulae used to validate a variety of identification numbers. In financial domain, this is typically used to verify the authenticity of tax registration numbers provided by companies in various financial transactions and tax departments use this for ensuring the integrity of the numbers declared by the tax assesses.

### **Other common ways to detect frauds and errors**

There are certain common ways by which an organization could pave the way for detecting some of the frauds and errors. These techniques are industry agnostic and could be adopted depending upon the needs of the organization. Below are some of the common techniques (non-exhaustive).

- Summarization – Aggregation of key data to detect initial patterns.
- Classification – Arranging data into homogenous groups or classes.
- Stratification – Variant of classification, involves further grouping of data into levels or bands.
- Odds – Reviewing the cause of missing sequences, duplicates, round numbers, outliers, etc.

## **4.2 Performance prediction**

One of the key functionalities of unconventional methods as explained earlier, is the ability to predict future financial behaviour there by enabling organizations to devise and execute strategies. Some of these prediction models may often require a lot of external data in addition to organizational data to better predict the future outcomes.

### Financial planning with predictive analytics

Traditional financial planning and budgeting techniques leverage only historic information with certain growth assumptions. Predictive analytics is an emerging area that helps financial planning and budgeting to better forecast financial outcomes. Predictions are derived based on historical data, statistical models and machine learning algorithms. Most common techniques include the following:

|   |                             |  |
|---|-----------------------------|--|
| 1 | Time series analysis        | Models like ARIMA, SARIMA, etc, are used to forecast values based on time-series data.   |
| 2 | Regression analysis         | Multiple regression models including logistic and linear regression help to predict financial outcomes by establishing a relationship between variables, e.g. revenue vs. marketing spend. |
| 3 | Machine learning models     | Machine learning algorithms such as random forests, gradient boosting machines, neural networks, etc. could be used for more complex patterns and non-linear relationships in the data.    |
| 4 | Monte carlo simulation      | Used to model the probability of different outcomes.   |
| 4 | Clustering techniques       | Clustering techniques such as K-Means are used for identifying customer segments or spending patterns.   |
| 5 | Natural language processing | Analyzes text data from news, reports and social media to predict behaviours or sentiment having an impact on financial planning.  |

### Altman's Z-score for business solvency prediction

Designed to predict the likelihood of financial distress or bankruptcy mainly of publicly traded manufacturing companies. The score, i.e. Z-score or "distress score" is based on a combination of financial ratios that are indicative of a company's financial health.

$Z\text{-score} = 1.2(\text{working capital}/\text{total assets}) + 1.4(\text{retained earnings}/\text{total assets}) + 3.3(\text{EBIT}/\text{total assets}) + 0.6(\text{market value of equity}/\text{total liabilities}) + 1.0(\text{sales}/\text{total assets})$

Generally, the lower the score, the higher the probability of distress. Specifically, the score could be interpreted as:

- Score < 1.81 – High probability of distress
- Score > 1.81 > 2.99 – Grey zone, i.e. not a strong predictor
- Score > 2.99 – Low probability of distress

This model is primarily used by investment companies who would want to assess the liquidity position of the "target companies" amongst other matters before an investment decision is made.

## 4.3 Risk management

Risk management is one of the most emerging as well as advanced and most sought-after areas for the application of financial analytics. According to a recent survey conducted by KPMG covering 400 senior executives across the globe, 61% of the respondents expected to see a significant increase in the level of risk they will be responsible for in the next 3 to 5 years. 78% of the respondents' report using data analytics, AI and machine learning to streamline and improve risk management (KPMG, 2024, Future

of Risk – Building a trusted risk function to succeed in a riskier world).

A few of the key risk management application areas are explained below.

### **Credit risk management**

One of the critical elements of risk management is to effectively manage the credit risk which is primarily concerned with managing the risk of payment default by the customers. Quite a lot of efforts are made by organizations to effectively manage this risk by establishing a credit scoring mechanism which include the prediction of the likelihood of customer making default. Advanced machine learning models are leveraged, which analyzes customer behaviour, prior patterns and general economic conditions to predict the likelihood of default. Even though every organization is concerned with credit risk management, this advanced area is primarily leveraged by organizations in the banking and financial services industry.

### **Regulatory risk management**

Regulators and industries with a lot of regulatory reporting and compliance will be obliged to ensure the accuracy of information being reported. Analytics and machine learning could be deployed to automate and enhance the accuracy of reporting. These applications could identify suspicious transactions, detect any patterns of anti-money laundering which enables the organization to either report or investigate these patterns.

### **Liquidity risk management**

Liquidity is of key concern to almost all the business organizations and managing its risk is of prime importance especially to large corporations and financial institutions. Liquidity risk is primarily managed through continuous analysis of cash flows and transactions as well as through review of general market conditions. In financial institutions, it is also a common practice to perform stress testing, which is a variant of scenario analysis by evaluating how adverse market conditions (e.g. sudden withdrawal of funds) might impact on the organization's liquidity position.

### **Other application areas in risk management (non-exhaustive)**

|   |                              |  |
|---|------------------------------|--|
| 1 | Supply chain risk management | Predictive analytics could be leveraged to anticipate demand changes and optimizing the inventory levels to reduce the risks of excess inventory or outages.   |
| 2 | Insurance risk management    | Using data analytics and anomaly detection techniques, fraudulent claims could be identified by the insurance companies. Also, predictive models could be deployed to assess risk profiles that aids setting the optimum price for insurance products, by optimizing profits and risk. |
| 3 | Enterprise risk management   | Through integration of structured data (i.e. financials and related information) and unstructured data (e.g. content from news feeds, social media, etc.), emerging risks across different domains could be identified.  |

## 5. PRE-REQUISITES FOR PERFORMING UNCONVENTIONAL ANALYTICS

Before embarking on any data analytics journey, the organization will have to ensure certain basic infrastructure in place. This includes sufficient defining the objective and ask from the analytics, data availability, adequate IT platforms, necessary skillsets to understand visualize and interpret data. There are certain other attributes that organizations need to bear in mind if they are in for the application of unconventional analytics. These are not just for finance domain, but at a minimum, this covers the following:

- **“One team” mindset** – Since analytics of this sort involves a lot of cross functional data not just restricted to finance, organization need to have a “one team” mindset rather than working in a siloed or functional mindset.
- **Data quality** – Unconventional analytics rely on vast amounts of data gathered from different sources both within and outside the organization. This data could include financial, operational and external data. Data should also be of adequate quality to perform any meaningful analyses. The common phrase of “garbage-in-garbage-out” holds true here as well.
- **Data governance** – Organizations need to put in place the right data governance mechanisms to ensure that there are no data breaches and all necessary regulatory compliances in this regard are met.
- **IT infrastructure** – Organization should have adequate IT infrastructure to extract and handle big data, run required algorithms / computations and perform meaningful visualizations and outputs.
- **Skillsets** – Most of the unconventional methods rely upon leveraging statistical, quantitative and machine learning capabilities. Hence, organizations need to ensure that they have the right people with adequate expertise, including required domain knowledge. As per a recent study conducted by Gartner, by 2027 50% of data analysts will be retrained as data scientists and data scientists will shift to become AI engineers (Gartner, June 2024, Over 100 Data Analytics and AI Predictions Through 2030)
- **Patience and “iterative” mindset** – Organizations need to have the required patience and provide all the organizational infrastructure before reaping the benefits of this sort of advanced analytics. Typically, these kinds of analytics consume a reasonable amount of time before stabilization and the final solution will be reached after having decent rounds of iterations as is the case with any typical machine learning project.

## 6. RECAP AND KEY TAKEAWAYS

- Advancements made in the field of analytics and machine learning are increasing the need for finance to focus its analysis not just on what had happened in the past but also on forecasting what the future looks like.
- Earlier, analytics for finance was mostly centered around conventional methods that rely primarily on historical data and information. With the increasing need to focus on providing a forward-looking view, finance is adopting advanced and unconventional ways to perform analytics.
- These methods rely on huge amounts of organizational data, various external data, statistical and quantitative models.
- Before embarking on the journey to perform these advanced analytics organizations need to have certain pre-requisites to achieve the desired outcomes. These pre-requisites include one team mindset, data quality & governance, availability of IT infrastructure and required skillsets, etc.



## 7. REFERENCE

1. “Garner Finance Predicts – Leadership Vision for 2024 – Top 5 Strategic Priorities for Heads of Financial Planning & Analysis”. Gartner. 2024. Retrieved on 4 September 2024 from <https://www.gartner.com/en/finance/trends/leadership-vision-financial-planning-analysis>
2. “Financial Theory Evolution”. International Journal of Education and Research. 2013. Retrieved on 17 October from [https://www.researchgate.net/publication/256062706\\_Financial\\_Theory\\_Evolution/link/5b96d7e64585153a531feedd/download](https://www.researchgate.net/publication/256062706_Financial_Theory_Evolution/link/5b96d7e64585153a531feedd/download)
3. “Finance 2030: Four Imperatives for the next decade”. McKinsey & Company. November 2020. Retrieved on 4 September 2024 from <https://www.mckinsey.com/capabilities/operations/our-insights/finance-2030-four-imperatives-for-the-next-decade>
4. “Occupational Fraud 2024 – A Report to the Nations”. Association of Certified Fraud Examiners. 2024. Retrieved on 4 September 2024 from <https://legacy.acfe.com/report-to-the-nations/2024/>
5. “Future of Risk – Building a trusted risk function to succeed in a riskier world”. KPMG. 2024. Retrieved on 4 September 2024 from <https://kpmg.com/xx/en/home/insights/2024/07/future-of-risk.html>
6. “Data, BI and Analytics Trend Monitor-2024”. BARC. 2023. Retrieved on 4 September 2024 from [https://pages.barc.de/hubfs/Marketing/Reports/Data%2c%20BI%20and%20Analytics%20Trend%20Monitor%202024.pdf?utm\\_campaign=2019-12\\_Trends&utm\\_medium=email&hsenc=p2ANqtz-  
\\_ISDIn6KWQgaHLkJFx1PnZAmXCufwmBPq6UUhcB6djULNnkVkVn2CnKEIOQwCqvE6RGF9\\_c6hXWsAE1bgi  
uFcEBGwP\\_vQt0G6ADuMH99qp0yV3QU&hsmi=285426237&utm\\_content=285426237&utm\\_source=hs\\_automati  
on](https://pages.barc.de/hubfs/Marketing/Reports/Data%2c%20BI%20and%20Analytics%20Trend%20Monitor%202024.pdf?utm_campaign=2019-12_Trends&utm_medium=email&hsenc=p2ANqtz-<br/>_ISDIn6KWQgaHLkJFx1PnZAmXCufwmBPq6UUhcB6djULNnkVkVn2CnKEIOQwCqvE6RGF9_c6hXWsAE1bgi<br/>uFcEBGwP_vQt0G6ADuMH99qp0yV3QU&hsmi=285426237&utm_content=285426237&utm_source=hs_automati<br/>on)

\*\*\*\*\*