



# DATA ANALYTICS

## Quick Reference Guide

[www.gsdccouncil.org](http://www.gsdccouncil.org) Data Insights



# What is Data Analytics?

Data Analytics involves examining raw data to uncover meaningful patterns, trends, correlations, and insights that support business objectives. At its core, data analytics transforms raw numbers and text into actionable knowledge – enabling organizations to move from gut-feel decisions to evidence-based strategies.

## Core Definition

The systematic process of inspecting, cleansing, transforming, and modeling data to discover useful information, draw conclusions, and support decision-making across all levels of an organization.

## Objectives of Data Analytics

- Improve decision-making at all organizational levels
- Identify emerging opportunities and manage risks proactively
- Optimize business processes and reduce operational waste
- Enhance customer experiences through personalization
- Increase operational efficiency and resource allocation
- Support long-term strategic planning with evidence

**i** Data analytics is not just a technical discipline – it is a strategic capability that separates high-performing organizations from their competitors. Analysts who can translate data into business value are among the most sought-after professionals today.

# Types of Data Analytics

The four types of data analytics represent a progressive spectrum – from understanding the past to shaping the future. Each type answers a different business question and requires different tools and techniques. Mastering all four enables analysts to provide comprehensive, end-to-end analytical support.

## 1. Descriptive Analytics

**Purpose:** Understand what happened.

- What occurred?
- What were the results?
- What trends exist?

**Examples:** Monthly sales reports, customer activity summaries, website traffic reports.

## 2. Diagnostic Analytics

**Purpose:** Understand why something happened.

- Why did sales decrease?
- Why did customer churn increase?

**Techniques:** Root Cause Analysis, Correlation Analysis, Drill-Down Analysis.

# Predictive & Prescriptive Analytics

The more advanced tiers of analytics move beyond historical explanation into forward-looking intelligence. Predictive analytics leverages statistical models and machine learning to anticipate future outcomes, while prescriptive analytics goes one step further – recommending specific actions to achieve desired results. Together, these two types transform analytics from a reporting function into a strategic decision-making engine.

## 3. Predictive Analytics

**Purpose:** Forecast future outcomes.

- What is likely to happen?
- What trends may emerge?

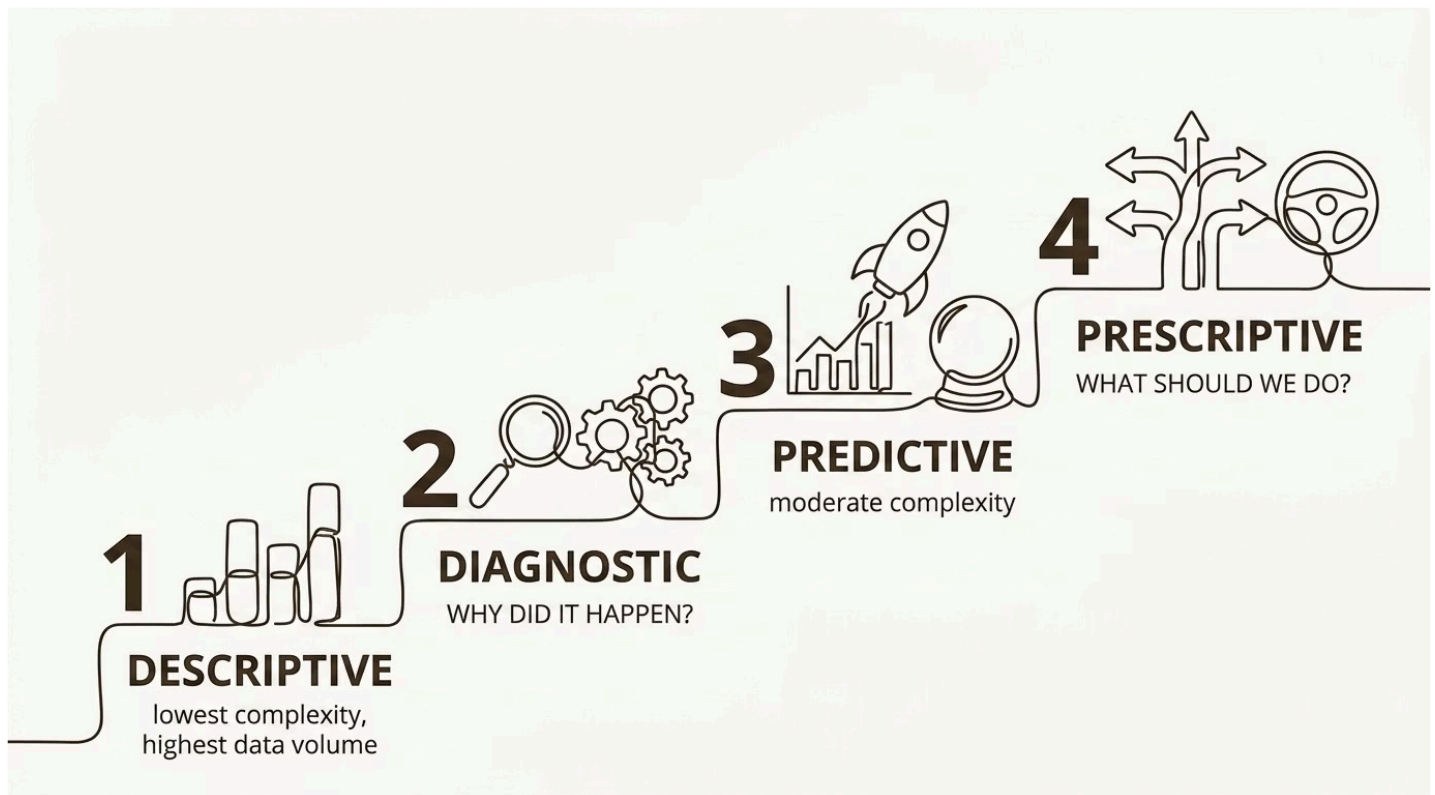
**Techniques:** Regression Analysis, Forecasting Models, Machine Learning Models.

## 4. Prescriptive Analytics

**Purpose:** Recommend specific actions.

- What should we do next?
- Which decision produces the best outcome?

**Techniques:** Optimization Models, Decision Analysis, Simulation.



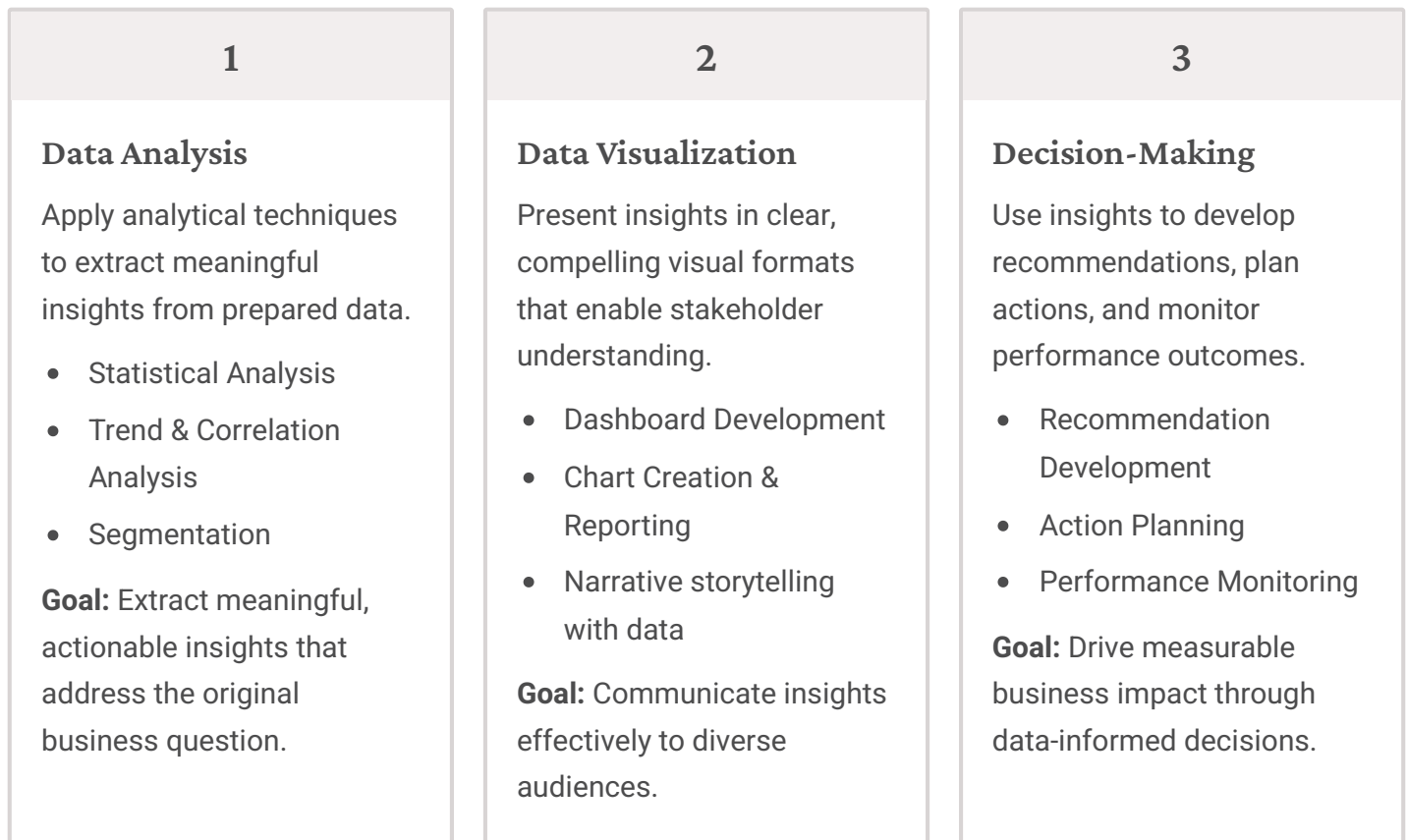
# Data Analytics Lifecycle — Part 1

The Data Analytics Lifecycle provides a structured framework for approaching any analytical problem systematically. Following this lifecycle ensures that analysis is grounded in business context, supported by quality data, and ultimately actionable. The first three steps lay the critical foundation upon which all subsequent analysis depends – skipping or rushing these phases is one of the most common causes of analytical failure.

1	2	3
<p><b>Business Understanding</b></p> <p>Define objectives, identify stakeholders, and establish success criteria before touching any data.</p> <ul style="list-style-type: none"><li>• Define objectives clearly</li><li>• Identify key stakeholders</li><li>• Establish measurable success criteria</li></ul> <p><b>Deliverables:</b> Problem Statement, Business Requirements Document</p>	<p><b>Data Collection</b></p> <p>Gather relevant and reliable data from all applicable sources to support the analytical objective.</p> <ul style="list-style-type: none"><li>• Databases, CRM &amp; ERP Systems</li><li>• APIs, Surveys, Web Analytics</li><li>• IoT Devices and external feeds</li></ul> <p><b>Goal:</b> Collect relevant, reliable, and representative data.</p>	<p><b>Data Preparation</b></p> <p>Clean, transform, validate, and integrate data to ensure it is analysis-ready.</p> <ul style="list-style-type: none"><li>• Handle missing values and duplicates</li><li>• Resolve inconsistent formats</li><li>• Detect and treat outliers</li></ul> <p><b>Common Issues:</b> Missing values, duplicate records, inconsistent formats, outliers.</p>

# Data Analytics Lifecycle — Part 2

With clean, well-prepared data in hand, analysts move into the analytical and communication phases of the lifecycle. Data analysis extracts insights from the data, visualization communicates those insights to stakeholders, and decision-making translates insights into action. These three steps are where analytical value is ultimately delivered and measured – making them the most visible and business-critical phases of the process.



# Data Types

Understanding the different types of data is fundamental to selecting appropriate analytical methods and tools. Data exists in three primary forms – structured, unstructured, and semi-structured – each presenting unique opportunities and challenges for analytics. The majority of enterprise data today is unstructured, making the ability to work across all three types an increasingly critical skill for modern analysts.



## Structured Data

Organized and stored in predefined formats, typically in relational databases or spreadsheets. Easiest to query and analyze using standard tools.

- Relational Databases (SQL)
- Excel Tables & CSV Files
- Transaction Records



## Unstructured Data

Does not follow predefined structures. Represents approximately 80% of all data generated today. Requires advanced techniques such as NLP or computer vision to analyze.

- Emails, Social Media Posts
- Videos, Images, Audio
- PDFs and Documents



## Semi-Structured Data

Contains organizational properties such as tags or markers, but lacks the rigid structure of a relational database. Common in modern web applications and data exchange formats.

- JSON & XML Files
- Log Files
- Email with metadata

# Key Statistical Concepts — Central Tendency

Statistical literacy is a cornerstone of effective data analytics. Understanding measures of central tendency — mean, median, and mode — allows analysts to summarize datasets, identify typical values, and spot anomalies. These three measures each tell a different story about a dataset, and knowing when to use each one is essential for accurate interpretation and reporting.

## Mean — Arithmetic Average

The mean is calculated by summing all values in a dataset and dividing by the count of values. It is the most commonly used measure of central tendency but is sensitive to extreme values (outliers).

**Formula:** Mean = Sum of Values ÷ Number of Values

**Best used when:** Data is symmetrically distributed without significant outliers.

## Median — Middle Value

The median is the middle value when a dataset is sorted in ascending or descending order. For even-numbered datasets, the median is the average of the two middle values. The median is resistant to outliers, making it more reliable for skewed distributions.

**Best used when:** Data contains outliers or is skewed (e.g., income data, housing prices).

## Mode — Most Frequent Value

The mode is the value that appears most frequently in a dataset. A dataset can have no mode, one mode (unimodal), or multiple modes (bimodal, multimodal). The mode is the only central tendency measure applicable to categorical data.

**Best used when:** Identifying the most common category, preference, or occurrence in a dataset.

# Key Statistical Concepts — Variability

Measures of variability describe how spread out or dispersed data values are around the central tendency. While measures of central tendency tell you where data is centered, measures of variability tell you how reliable and consistent that center is. Range and standard deviation are the two most frequently used variability measures in business analytics contexts.

## Range

The simplest measure of variability — the difference between the highest and lowest values in a dataset.

**Formula:** Range = Maximum – Minimum

**Limitation:** Range is sensitive to extreme outliers and provides no information about the distribution of values between the extremes. Use as a quick first check, not as a sole measure of spread.

## Standard Deviation

Measures how much individual data points deviate from the mean on average. It is the square root of the variance and is expressed in the same units as the original data.

- **Low SD:** Data is clustered closely around the mean — high consistency
- **High SD:** Data is spread widely — high variability

Standard deviation is widely used in quality control, risk assessment, financial analysis, and performance benchmarking.

- A practical rule of thumb: in a normal distribution, approximately 68% of values fall within one standard deviation of the mean, 95% within two, and 99.7% within three — known as the Empirical Rule.

# Probability Basics

Probability is the mathematical foundation of predictive analytics and statistical inference. It quantifies uncertainty – expressing the likelihood that a specific event will occur as a number between 0 (impossible) and 1 (certain). Every predictive model, hypothesis test, and confidence interval is built on probability principles. Understanding these fundamentals is essential for any analyst working with forecasting, risk assessment, or machine learning models.

Probability Scale	Core Formula	Practical Applications
<b>0</b> = Impossible (will never happen) <b>0.5</b> = Equal chance (50/50) <b>1</b> = Certain (will always happen)	<b>Probability = Favorable Outcomes ÷ Total Outcomes</b>  Example: Probability of rolling a 3 on a six-sided die = $1 \div 6 \approx 0.167$ (16.7%)	<ul style="list-style-type: none"><li>• Customer churn prediction</li><li>• Fraud detection scoring</li><li>• A/B test significance</li><li>• Risk assessment models</li></ul>

# Correlation Analysis

Correlation analysis measures the strength and direction of the relationship between two variables. It is one of the most widely used techniques in exploratory data analysis, helping analysts quickly identify which variables are related before building more complex models. Understanding correlation is also essential for avoiding one of the most common analytical errors: confusing correlation with causation – two variables can be correlated without one causing the other.



## Positive Correlation

As one variable increases, the other also increases. The relationship moves in the same direction.

**Example:** Advertising spend and sales revenue – more spend typically yields higher revenue.



## Negative Correlation

As one variable increases, the other decreases. The relationship moves in opposite directions.

**Example:** Price increases and demand – higher prices typically reduce purchase volume.



## No Correlation

No discernible relationship exists between the two variables. Changes in one do not predict changes in the other.

**Example:** Shoe size and job performance – no meaningful relationship.

Coefficient Value	Interpretation
+1.0	Perfect Positive Correlation
+0.7 to +0.9	Strong Positive Correlation
+0.4 to +0.6	Moderate Positive Correlation
0	No Correlation
-0.4 to -0.6	Moderate Negative Correlation
-1.0	Perfect Negative Correlation

# Data Cleaning Techniques

Data cleaning – also called data cleansing or data scrubbing – is the process of detecting and correcting errors, inconsistencies, and inaccuracies in datasets before analysis. It is widely cited as the most time-consuming step in the analytics process, often accounting for 60–80% of an analyst's time. The investment is critical, however: analysis built on dirty data produces unreliable insights regardless of how sophisticated the analytical techniques used.



## Missing Value Treatment

- Remove incomplete records
- Replace with mean or median
- Predict missing values using models
- Flag as a separate category



## Duplicate Removal

Eliminate exact or near-duplicate records to prevent double-counting and improve analysis accuracy. Deduplication is especially critical in CRM and customer datasets.



## Outlier Detection

Identify unusual values that may distort statistical measures.

- Z-Score method
- IQR (Interquartile Range) method
- Visual inspection via box plots



## Standardization

Ensure consistent formats, units, and coding conventions throughout the dataset. Examples: date formats (MM/DD/YYYY vs. DD/MM/YYYY), currency units, category labels.

# Common Data Analysis Techniques

Analytical technique selection should be driven by the type of business question being answered and the structure of available data. The five techniques below represent the core toolkit for most business analytics work – from simple trend monitoring to complex causal investigations. Proficiency in applying and interpreting each technique is expected of professional analysts and is a frequent focus of analytics certification exams.

## **Trend Analysis**

Examines how a metric changes over a defined time period. Used to identify growth patterns, seasonal fluctuations, and long-term directional shifts. Essential for sales forecasting, KPI monitoring, and strategic planning.

## **Segmentation Analysis**

Groups data into meaningful subsets based on shared characteristics. Common applications include customer segmentation (demographic, behavioral, geographic), product category analysis, and market segmentation. Enables targeted strategies for each distinct group.

## **Cohort Analysis**

Analyzes the behavior of groups (cohorts) that share a common characteristic – typically an acquisition date or first-purchase period – over time. Widely used for customer retention analysis, lifetime value estimation, and product engagement studies.

## **Root Cause Analysis**

A diagnostic technique that systematically identifies the underlying causes of a problem rather than its symptoms. Common tools include the 5 Whys framework, fishbone (Ishikawa) diagrams, and Pareto analysis.

## **Regression Analysis**

Examines the statistical relationship between a dependent variable and one or more independent variables. Linear regression predicts continuous outcomes; logistic regression predicts binary outcomes. Foundational to both diagnostic and predictive analytics.

# Data Visualization Principles

Effective data visualization transforms complex analytical findings into clear, compelling visuals that stakeholders can understand and act upon. The goal is not decoration – it is communication. Choosing the right chart type for the right data relationship is one of the most impactful skills an analyst can develop. The following chart types represent the essential visualization toolkit for business analytics professionals.



## Bar Chart

Best for comparing discrete categories side by side. Use horizontal bars when category names are long.



## Line Chart

Ideal for showing trends, changes, and patterns over a continuous time period.



## Pie Chart

Displays part-to-whole proportions. Best limited to 5 or fewer categories for clarity.



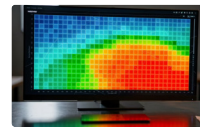
## Scatter Plot

Reveals relationships and correlations between two continuous variables. Ideal for identifying clusters and outliers.



## Histogram

Shows the frequency distribution of a single continuous variable. Used to assess data shape and spread.



## Heat Map

Uses color intensity to highlight patterns, concentrations, and anomalies across two-dimensional data matrices.

# Dashboard Design Best Practices

A well-designed dashboard is one of the most powerful tools an analyst can deliver. It provides stakeholders with real-time visibility into the metrics that matter most – without requiring them to run their own queries or interpret raw data. However, poor dashboard design can actively mislead or overwhelm users. The following principles guide analysts in creating dashboards that inform and empower rather than confuse.

1

## Keep It Simple

Eliminate chart junk, unnecessary decorations, and redundant data. Every element on a dashboard should earn its place by serving a specific communicative purpose. Complexity is the enemy of insight.

2

## Highlight Key Metrics

Design around the 3–5 most critical KPIs. Use visual hierarchy – size, color, and position – to draw attention to the most important metrics first. Place high-priority KPIs in the top-left where the eye naturally lands.

3

## Use Consistent Formatting

Apply a unified color palette, typography, and labeling system throughout the dashboard. Inconsistent formatting forces users to re-learn the visual language on every chart, increasing cognitive load and reducing comprehension speed.

4

## Enable Interactivity

Incorporate filters, drill-downs, and date range selectors to support self-service data exploration. Interactivity transforms a static report into a dynamic analytical tool that empowers stakeholders to answer their own follow-up questions.

# Key Performance Indicators (KPIs)

KPIs are quantifiable measures that evaluate how effectively an organization is achieving its key business objectives. Unlike general metrics, KPIs are tied to specific strategic goals and are used to track performance, drive accountability, and signal when corrective action is needed. Effective KPIs are SMART: Specific, Measurable, Achievable, Relevant, and Time-bound. The following examples illustrate KPIs across three critical business functions.

## Sales KPIs

- **Revenue:** Total sales generated in a period
- **Conversion Rate:** % of leads that become customers
- **Average Order Value:** Mean revenue per transaction
- **Sales Growth Rate:** Period-over-period revenue change

## Marketing KPIs

- **CAC:** Customer Acquisition Cost
- **CTR:** Click-Through Rate on campaigns
- **ROAS:** Return on Ad Spend
- **Lead Generation Volume:** Qualified leads per period

## Customer Service KPIs

- **CSAT:** Customer Satisfaction Score
- **Resolution Time:** Average time to resolve issues
- **Retention Rate:** % of customers retained over time
- **NPS:** Net Promoter Score

- A KPI dashboard should be reviewed regularly – not just when something goes wrong. Proactive monitoring enables early intervention before small deviations become significant problems.

# Business Intelligence (BI)

Business Intelligence is the umbrella discipline that encompasses the strategies, processes, technologies, and tools used to collect, integrate, analyze, and present business information. BI transforms raw operational data into meaningful, actionable intelligence that supports strategic, tactical, and operational decision-making across all levels of an organization. While data analytics focuses on answering specific questions through analysis, BI is more broadly concerned with creating persistent reporting infrastructure and enabling ongoing data-driven culture.

## BI Combines Four Pillars

- Data Collection from multiple sources
- Analysis of consolidated data
- Reporting for stakeholder consumption
- Visualization for rapid comprehension

Together, these pillars enable informed, timely, and evidence-based business decisions.

## Common BI Tools

### Microsoft Power BI

Industry-leading BI platform with deep Microsoft ecosystem integration. Widely used in enterprise environments.

### Tableau

Renowned for visual analytics capabilities and drag-and-drop dashboard creation. Popular in analytics-forward organizations.

### Qlik Sense

Known for associative data modeling and powerful self-service analytics features.

### Looker

Google-backed BI platform excelling in data modeling and embedded analytics use cases.

# SQL Essentials for Analysts

Structured Query Language (SQL) is the universal language of data – the single most important technical skill for data analysts across virtually every industry and tool stack. Even analysts who primarily work in BI tools like Tableau or Power BI benefit enormously from SQL proficiency, as it enables direct database interaction, faster troubleshooting, and deeper understanding of how data is structured and stored. The four commands below represent the foundation of analytical SQL work.

## SELECT — Retrieve Data

The fundamental command for extracting data from a database table. The asterisk (\*) selects all columns; specify column names for targeted retrieval.

```
SELECT * FROM customers;
```

## WHERE — Filter Data

Filters query results based on specified conditions. Supports multiple conditions using AND/OR operators. Essential for retrieving specific subsets of data.

```
SELECT * FROM customers WHERE  
country = 'India';
```

## GROUP BY — Aggregate Data

Groups rows with identical values in specified columns and applies aggregate functions (COUNT, SUM, AVG, MAX, MIN) to each group. Foundational for summary reporting.

```
SELECT department, COUNT(*) FROM  
employees GROUP BY department;
```

## ORDER BY — Sort Results


Sorts query results by one or more columns in ascending (ASC) or descending (DESC) order. Critical for ranked lists, top-N analysis, and readable reports.

```
SELECT * FROM sales ORDER BY  
revenue DESC;
```

# Excel Functions for Analytics

Microsoft Excel remains one of the most widely used analytical tools in business environments worldwide. Proficiency in Excel's core analytical functions accelerates day-to-day analysis, enables rapid prototyping of analytical models, and is frequently tested in analytics certifications. The functions below represent the essential Excel toolkit for any professional analyst – from basic aggregations to advanced lookup and summarization capabilities.

Function	Purpose	Use Case
SUM()	Add a range of numeric values	Total revenue calculation
AVERAGE()	Calculate the arithmetic mean	Average order value
COUNT()	Count numeric entries in a range	Transaction volume
IF()	Apply conditional logic	Flag above/below threshold
VLOOKUP()	Vertical lookup by key value	Product price lookup
XLOOKUP()	Advanced lookup – any direction	Flexible reference matching
INDEX()	Return value at row/column position	Dynamic range reference
MATCH()	Find position of a value in range	Combined with INDEX()
PIVOT TABLE	Summarize and cross-tabulate data	Sales by region/product

 The INDEX/MATCH combination is generally preferred over VLOOKUP for its flexibility – it can look left, handle column insertions gracefully, and is faster on large datasets.

# Data Governance Basics

Data Governance is the framework of policies, processes, standards, and accountability structures that ensure data is managed as a trusted organizational asset. Without effective governance, organizations face data quality degradation, compliance risks, security vulnerabilities, and loss of stakeholder trust in analytical outputs. As data volumes continue to grow exponentially, governance has evolved from a back-office concern into a board-level strategic priority – particularly in regulated industries such as finance, healthcare, and government.

## Data Quality

Ensuring that data is accurate, complete, consistent, and fit for its intended use across all systems.

## Data Security

Protecting data from unauthorized access, breaches, and misuse through access controls and encryption.

## Data Consistency

Maintaining uniform definitions, formats, and values across all systems and business units.

## Data Compliance

Adhering to regulatory requirements such as GDPR, HIPAA, CCPA, and industry-specific standards.

## Data Ownership

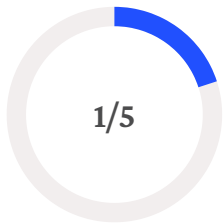
Clearly assigning responsibility for data assets to accountable business owners and stewards.

## Key Governance Components

- **Policies:** Rules governing data use, access, and retention
- **Standards:** Definitions, formats, and naming conventions
- **Stewardship:** Designated owners responsible for data domains
- **Monitoring:** Ongoing audits and quality checks to sustain compliance

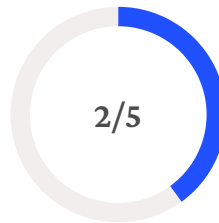
# Data Quality Dimensions

Data quality is multidimensional – a dataset can be accurate but incomplete, or complete but outdated. Evaluating data quality requires assessing it across five key dimensions, each of which measures a distinct aspect of fitness for use. Understanding these dimensions helps analysts identify specific quality issues, communicate data limitations to stakeholders, and prioritize data remediation efforts effectively.



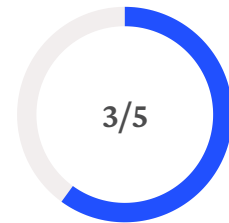
## Accuracy

Data correctly reflects the real-world entity or event it represents. Inaccurate data leads directly to flawed analysis and misguided decisions.



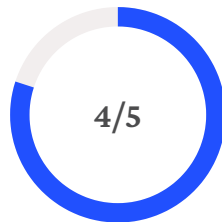
## Completeness

All required data fields and records exist. Incomplete data creates gaps in analysis and may introduce systematic bias.



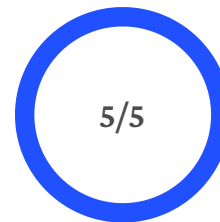
## Consistency

Data values and definitions match across all systems, tables, and business units. Inconsistency is a common symptom of data silos.



## Validity

Data conforms to defined business rules, formats, and permissible value ranges. Invalid data passes basic existence checks but fails logical validation.



## Timeliness

Data is current and available when needed. Stale data can be accurate and complete yet still lead to incorrect conclusions about present conditions.

# Ethics in Data Analytics


As data analytics capabilities grow more powerful, the ethical responsibilities of analysts grow in parallel. Analytical decisions – from how data is collected to how models are deployed – can have profound impacts on individuals, communities, and societies. Ethical analytics practice requires deliberate attention to fairness, transparency, privacy, and accountability at every stage of the analytical lifecycle. Regulatory frameworks such as GDPR, CCPA, and emerging AI ethics standards are increasingly codifying these principles into legal requirements.

## Core Ethical Principles

- **Transparency:** Be clear about data sources, methods, and limitations
- **Fairness:** Ensure models and insights do not discriminate against protected groups
- **Privacy Protection:** Handle personal data with care, minimizing collection and maximizing security
- **Responsible Data Usage:** Use data only for its intended and consented purpose

## Critical Considerations


- **Data Bias:** Biased training data produces biased outputs – actively test for and mitigate bias in analytical models
- **Consent:** Individuals should understand and agree to how their data is being collected and used
- **Confidentiality:** Protect sensitive information and apply appropriate anonymization techniques
- **Regulatory Compliance:** Stay current with GDPR, HIPAA, CCPA, and sector-specific regulations

 Data bias is one of the most insidious risks in analytics. A model trained on biased historical data will perpetuate and amplify those biases at scale – often invisibly. Bias auditing should be a standard step in any model development process.

# Common Analytics Challenges

Even experienced analysts regularly encounter obstacles that threaten the validity, timeliness, and impact of their work. Recognizing these challenges in advance — and knowing proven strategies to address them — is a hallmark of analytical maturity. The following challenge-solution pairs represent the most frequently encountered issues in professional analytics environments and the practical approaches used to overcome them.

Challenge	Root Cause	Solution
Poor Data Quality	Inadequate data entry controls and validation rules at the source	Systematic data cleaning processes and source-level quality controls
Missing Data	Incomplete records from collection gaps or system failures	Implement validation rules; use imputation techniques for analysis
Data Silos	Disconnected systems without shared data infrastructure	Data integration platforms, data warehouses, and unified data models
Lack of Business Context	Analysts working in isolation from business stakeholders	Regular stakeholder collaboration, requirements workshops, and domain immersion
Visualization Overload	Too many metrics and charts without clear prioritization	Simplified, purpose-designed dashboards with a clear hierarchy of insights
Slow Reporting Cycles	Manual data processes and inefficient pipelines	Automation of ETL processes and self-service BI enablement

 The most effective analysts treat challenges as diagnostic signals — each obstacle points to a gap in process, tooling, or collaboration that, once addressed, permanently improves analytical capability.

# Data Analytics Best Practices

Best practices in data analytics represent the accumulated wisdom of the profession – the habits and disciplines that consistently separate high-quality analytical work from mediocre output. These practices apply at every stage of the analytical process: before the first query is written, during the analytical work itself, and after insights are delivered to stakeholders. Internalizing these practices accelerates professional development and builds credibility with business partners.

## Before Analysis

- Define clear, measurable objectives
- Understand and document stakeholder needs
- Verify and profile data quality before proceeding
- Align on success criteria and expected deliverables

## During Analysis

- Validate assumptions explicitly before relying on them
- Document methods, decisions, and transformations
- Use appropriate statistical techniques for the data type
- Conduct peer review or sanity checks on key findings

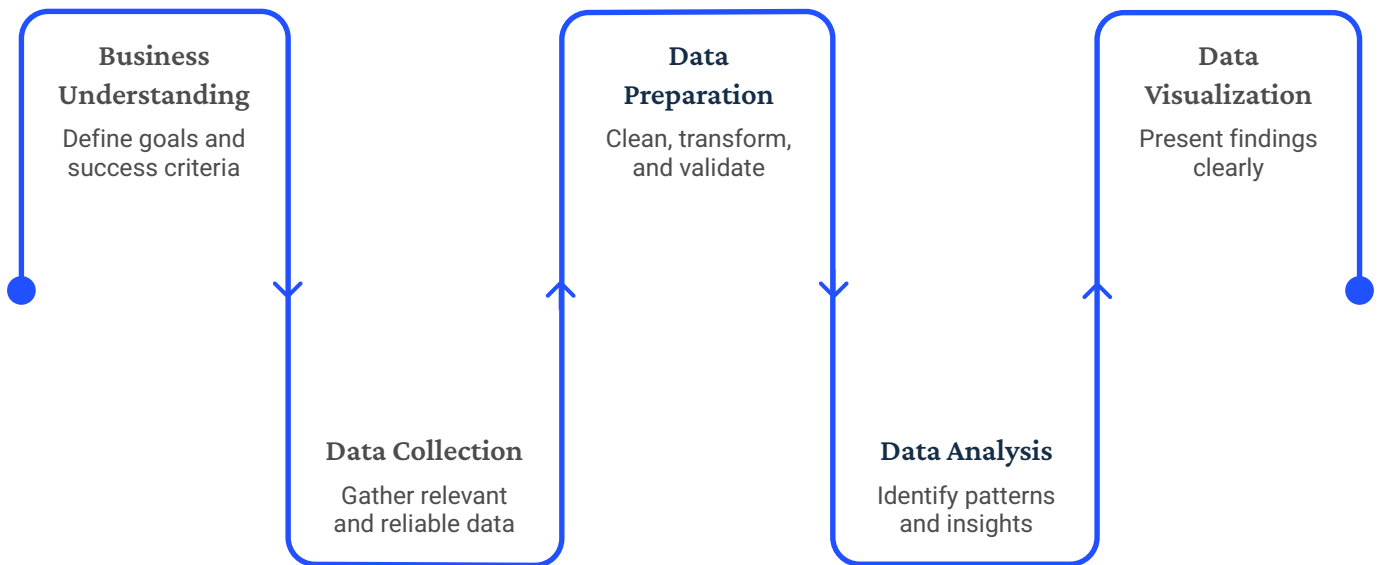
## After Analysis

- Communicate findings clearly — tailor to the audience
- Focus on actionable, decision-relevant insights
- Monitor outcomes to validate analytical recommendations
- Document and archive work for future reference

The goal of data analytics is not to produce analysis – it is to produce decisions. Every analytical deliverable should be evaluated against whether it moved the needle on a business outcome.

# Data Analytics Lifecycle Summary

The Data Analytics Lifecycle provides a repeatable, structured path from business problem to measurable impact. Each stage builds on the previous one – skipping steps compromises the integrity of the entire chain. This summary serves as a quick-reference reminder of the full lifecycle, the core activity at each stage, and the direction of flow from initial understanding to final action. Mastering this lifecycle is the foundation of professional analytics practice.



This end-to-end lifecycle applies whether you are running a simple monthly sales report or building an enterprise-scale predictive model. The rigor applied at each stage directly determines the quality and credibility of the final output.

**6**

## Lifecycle Stages

From business understanding through decision-making

**4**

## Analytics Types

Descriptive, Diagnostic, Predictive, Prescriptive

**5**

## Quality Dimensions

Accuracy, Completeness, Consistency, Validity,  
Timeliness

**3**

## Data Types

Structured, Unstructured, and Semi-Structured

- ✔ You have completed the Data Analytics Quick Reference Guide. Use this document as an ongoing reference during your analytical work and certification preparation. Return to individual sections whenever you need a fast, reliable refresher on any core concept.



# DATA ANALYTICS CERTIFICATION



## ABOUT GSDC CERTIFICATION



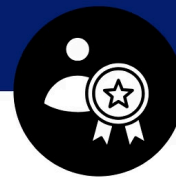
### EBOOK

Extensive and exclusive Ebook created by world's experts to help you with understanding core concepts.



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