Business Intelligence

ADDIS ABABA SCIENCE AND TECHNOLOGY UNIVERSITY
UNIVERSITY FOR INDUSTRY

Week 6

Business Analytics

- Descriptive analytics
- Diagnostic analytics
- Predictive analytics
- Prescriptive analytics
- Key Performance Indicators (KPIs)

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Objectives

At the end of this lecture students will be able to :

- Explain the concept of Business Analytics
- Differentiate the four types of analytics
- Apply analytics concepts to real-world scenarios
- Identify and design Key Performance Indicators (KPIs)
- Understand the analytics decision-making process

What is Business Analytics?

- Business Analytics (BA) is the systematic use of data, statistical analysis, and quantitative models to support decision-making and strategic planning.
- It transforms raw data → meaningful insights → actionable decisions.

Core Components of Business Analytics

- Data
  - Structured (databases, spreadsheets)
  - Semi-structured
  - Unstructured (text, social media, logs)
- Technology
  - Data warehouses, BI tools, analytics platforms
- Methods & Techniques
  - Statistics, machine learning, optimization
- Business Context
  - Organizational goals, strategy, domain knowledge

Provost, F., & Fawcett, T. (2013). Data science for business: What you need to know about data mining and data-analytic thinking. O'Reilly Media.

What is Business Analytics?

Business Analytics Process

1. Data collection
2. Data preparation (cleaning, integration)
3. Analysis & modeling
4. Interpretation of results
5. Decision-making

Example

- **Amazon**
  - Collects customer browsing and purchase data
  - Analyzes patterns using machine learning
  - Recommends products → increases sales

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Evolution of Analytics

- Analytics has evolved from basic reporting systems to advanced intelligent decision-making systems.
- **Reporting → BI → Advanced Analytics**
- This evolution reflects increasing:
  - Data volume
  - Computing power
  - Analytical sophistication

Shift in Decision-Making

From intuition-based decisions ➞ to data-driven decisions (DDD)

Key Drivers of Evolution

- Explosion of big data
- Advances in computing power (cloud, distributed systems)
- Increased business competition
- Demand for real-time insights

Davenport, T. H., & Harris, J. G. (2007). Competing on analytics: The new science of winning. Harvard Business School Press.

Types of Business Analytics

Type	Key Question	Description	Techniques	Example
Descriptive Analytics	What happened?	Summarizes historical data to understand past performance	Reporting, dashboards, aggregation	Monthly sales report
Diagnostic Analytics	Why did it happen?	Identifies root causes of events and patterns	Drill-down, correlation, data mining	Analyzing reasons for sales decline
Predictive Analytics	What will happen?	Uses statistical models to forecast future outcomes	Regression, classification, time series	Predicting customer churn
Prescriptive Analytics	What should we do?	Recommends optimal actions based on predictions	Optimization, simulation, decision models	Dynamic pricing strategies

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Analytics Value Chain

- The Analytics Value Chain describes how raw data is transformed into actionable insights and business value.
- It highlights the end-to-end process of analytics-driven decision-making

Stages of the Analytics Value Chain

1. **Data Collection**
    1. Sources: databases, sensors, transactions, social media
    2. Focus: acquiring relevant and high-quality data
2. **Data Processing & Preparation**
    1. Cleaning, integration, transformation
    2. Ensures data is accurate, consistent, and usable

Sharda, R., Delen, D., & Turban, E. (2014). Business intelligence and analytics: Systems for decision support (10th ed.). Pearson.

Analytics Value Chain…

Stages of the Analytics Value Chain

3. **Analysis & Modeling**
    1. Apply statistical and analytical techniques
    2. Includes descriptive, diagnostic, predictive methods
4. **Insight Generation**
    1. Interpret analytical results
    2. Identify patterns, trends, and relationships
5. **Decision-Making**
    1. Convert insights into **strategic or operational decisions**
6. **Action & Value Creation**
    1. Implement decisions
    2. Measure outcomes and business impact

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Descriptive Analytics

- Descriptive Analytics focuses on analyzing historical data to understand past performance.
- It answers the question: “What happened?”
- Forms the foundation for all other types of analytics.

Key Characteristics

- Uses structured data (e.g., databases, spreadsheets)
- Relies on aggregation and summarization
- Produces reports, dashboards, and visualizations
- Provides insight into trends and patterns

Provost, F., & Fawcett, T. (2013). Data science for business: What you need to know about data mining and data-analytic thinking. O’Reilly Media.

Descriptive Analytics…

Common Techniques & Tools

- Data aggregation (sum, average, counts)
- Data visualization (charts, dashboards)
- Basic statistics (mean, median, variance)
- Tools: Excel, SQL, Power BI, Tableau

Example

- A company generates a **monthly sales report** showing:
  - Total revenue
  - Sales by region
  - Top-performing products

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Diagnostic Analytics

- Diagnostic Analytics focuses on identifying the root causes of past events and outcomes.
- It answers the critical question: “Why did it happen?”
- Builds on descriptive analytics by moving from observation → explanation.

Key Characteristics

- Explores relationships and dependencies in data
- Uses drill-down and data discovery techniques
- Identifies patterns, anomalies, and correlations
- Supports problem-solving and decision-making

Han, J., Kamber, M., & Pei, J. (2012). Data mining: Concepts and techniques (3rd ed.). Morgan Kaufmann.

Diagnostic Analytics…

Core Techniques

- Drill-Down Analysis: Break data into finer levels (e.g., region → city → store)
- Correlation Analysis: Identify relationships between variables
- Root Cause Analysis: Determine underlying reasons for outcomes
- Data Mining: Discover hidden patterns in large datasets

Example

- A company observes a decline in sales (descriptive)
- Diagnostic analysis reveals:
    - Reduced demand in specific regions
    - Increased competitor activity
    - Supply chain delays

Han, J., Kamber, M., & Pei, J. (2012). Data mining: Concepts and techniques (3rd ed.). Morgan Kaufmann.

Predictive Analytics

- Predictive Analytics uses historical data, statistical models, and machine learning techniques to forecast future outcomes.
- It answers the question: “What is likely to happen?”
- Moves organizations from reactive → proactive decision-making.

Key Characteristics

- Relies on patterns and relationships in past data
- Produces probabilistic predictions (not certainties)
- Requires model training, validation, and testing
- Continuously improves as more data becomes available

Siegel, E. (2013). Predictive analytics: The power to predict who will click, buy, lie, or die. Wiley.

Predictive Analytics…

Core Techniques

- Regression Analysis: Predict continuous outcomes (e.g., sales forecasting)
- Classification Models: Predict categories (e.g., churn vs no churn)
- Time Series Analysis: Forecast trends over time
- Machine Learning Algorithms: Decision trees, random forests, neural networks

Example

- A company uses past customer data to:
  - Predict which customers are likely to leave (churn)
  - Forecast future product demand
  - Estimate revenue for the next quarter

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Predictive Analytics…

Case Study – Netflix

- Netflix is a global streaming platform serving millions of users with vast amounts of viewing and behavioral data.
- Success depends heavily on personalization and user engagement.

Application of Predictive Analytics

- Recommendation Systems
  - Predict what users are likely to watch next
  - Personalized homepage content
- User Behavior Prediction
  - Viewing patterns (time, genre preferences)
  - Content completion likelihood
- Churn Prediction
  - Identify users likely to cancel subscriptions
  - Enable proactive retention strategies

Techniques Used

- Collaborative filtering (user-item similarity)
- Classification models for churn prediction
- Machine learning algorithms for personalization

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Predictive Analytics…

Case Study – Banking Sector

- The banking industry generates large volumes of financial, transactional, and customer data.
- Predictive analytics is widely used to manage risk, detect fraud, and improve customer relationships.

Key Applications of Predictive Analytics

1. Credit Risk Assessment

- Predict likelihood of loan default
- Supports lending decisions
- Inputs:
    - Credit history
    - Income level
    - Repayment behavior

2. Fraud Detection

- Identify suspicious transactions in real time
- Detect unusual spending patterns

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Predictive Analytics…

Key Applications of Predictive Analytics

3. Customer Churn Prediction

- Predict which customers may leave
- Enable targeted retention strategies

4. Customer Segmentation

- Group customers based on behavior and value
- Support personalized marketing campaigns

Techniques Used

- Logistic regression (credit scoring)
- Classification models (fraud detection)
- Machine learning (pattern recognition)

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Prescriptive Analytics

- Prescriptive Analytics recommends optimal actions by combining:
  - Predictions (from predictive models)
  - Business rules/constraints
  - Optimization techniques
- It answers: “What should we do next?”
- Moves organizations from **insight → action → value creation**.

Key Characteristics

- Decision-oriented: produces recommended actions, not just insights
- Constraint-aware: incorporates limits (budget, capacity, regulations)
- Scenario-based: evaluates “what-if” alternatives
- Often automated/real-time in operational settings

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Prescriptive Analytics…

Core Techniques

- Optimization Models
  - Linear/Integer Programming for resource allocation
- Simulation
  - Monte Carlo or discrete-event simulation for uncertainty
- Decision Analysis
  - Decision trees, utility/risk trade-offs
- Rule-Based Systems
  - Business rules layered on predictions (e.g., thresholds, policies)

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Prescriptive Analytics…

Challenges

- Requires accurate input data and models
- Computationally intensive for large problems
- Difficult to model all real-world constraints

Winston, W. L. (2004). *Operations research: Applications and algorithms* (4th ed.). Thomson.

Case Study – Amazon

- Amazon operates a global e-commerce platform with complex supply chains, dynamic pricing, and massive customer demand variability.
- Prescriptive analytics is used to optimize decisions in real time.

Key Applications of Prescriptive Analytics

1. Dynamic Pricing

- Adjusts product prices based on:
  - Demand fluctuations
  - Competitor pricing
  - Customer behavior
- Goal: maximize revenue and competitiveness

2. Inventory Optimization

- Determines optimal stock levels across warehouses
- Balances:
  - Holding costs
  - Demand uncertainty

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Case Study – Amazon…

Key Applications of Prescriptive Analytics

3. Supply Chain & Logistics Optimization

- Optimizes:
  - Warehouse locations
  - Delivery routes
  - Order fulfillment strategies

4. Recommendation-Driven Decisions

- Uses predictive insights to guide:
  - Product recommendations
  - Marketing strategies

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Case Study – Telecom Industry

- Telecom operators manage complex, real-time networks serving millions of users.
- Challenges include:
  - Network congestion
  - Customer churn
  - Resource allocation
- Prescriptive analytics is used to optimize decisions under constraints.

Key Applications of Prescriptive Analytics

1. Network Traffic Optimization

- Dynamically routes traffic to reduce congestion
- Balances load across network nodes

2. Resource Allocation

- Allocates bandwidth and infrastructure efficiently
- Ensures quality of service (QoS) during peak usage

Winston, W. L. (2004). Operations research: Applications and algorithms (4th ed.). Thomson.

Case Study – Telecom Industry…

Key Applications of Prescriptive Analytics

3. Customer Retention Strategies

- Uses churn predictions to recommend:
  - Personalized offers
  - Data plans
  - Discounts

4. Pricing Optimization

- Designs flexible pricing plans based on:
  - Usage patterns
  - Customer segments

Winston, W. L. (2004). Operations research: Applications and algorithms (4th ed.). Thomson.

Integration of Analytics

- Effective organizations integrate all four analytics types into a continuous, end-to-end pipeline.
- This integration transforms data into progressively higher-value outputs: Descriptive → Diagnostic → Predictive → Prescriptive
- Data → Descriptive → Diagnostic → Predictive → Prescriptive → Decision → Action → Feedback

Role of Each Stage

- Descriptive: Summarizes past performance (What happened?)
- Diagnostic: Explains causes (Why did it happen?)
- Predictive: Forecasts future outcomes (What will happen?)
- Prescriptive: Recommends optimal actions (What should we do?)

Example

- Telecom company:
  - Reports high churn (Descriptive)
  - Identifies poor service quality (Diagnostic)
  - Predicts future churn rates (Predictive)
  - Recommends targeted retention offers (Prescriptive)

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Key Performance Indicators (KPIs)

- Key Performance Indicators (KPIs) are quantifiable metrics used to evaluate how effectively an organization achieves its strategic and operational goals.
- KPIs translate business objectives into measurable values.

Key Characteristics

- Aligned with strategy: Directly linked to organizational goals
- Quantifiable: Measurable using data
- Actionable: Enable decision-making and performance improvement
- Time-bound: Measured over specific periods

Types of KPIs

- Strategic KPIs: Long-term organizational performance (e.g., market share)
- Operational KPIs: Day-to-day performance (e.g., daily sales)
- Leading KPIs: Predict future performance (e.g., website traffic)
- Lagging KPIs: Reflect past performance (e.g., revenue)

Examples

- Revenue growth rate
- Customer retention rate
- Conversion rate (online sales)
- Average response time (service industry)

Parmenter, D. (2015). Key performance indicators: Developing, implementing, and using winning KPIs (3rd ed.). Wiley.

Characteristics of Effective KPIs (SMART Framework)

- Effective KPIs must be carefully designed to ensure they accurately measure performance and support decision-making.
- The SMART framework is widely used to evaluate KPI quality.

SMART Criteria

1. Specific
2. Measurable
3. Achievable
4. Relevant
5. Time-Bound

Example

- Poor KPI: “Improve customer satisfaction”
- SMART KPI:
  - “Increase customer satisfaction score from 75% to 85% within 12 months”

Parmenter, D. (2015). Key performance indicators: Developing, implementing, and using winning KPIs (3rd ed.). Wiley.

Case Study – Banking Sector KPIs

- Banks operate in a highly regulated, risk-sensitive environment where performance must be monitored across profitability, risk, and customer behavior.
- KPIs are essential for strategic decision-making, compliance, and operational control.

Parmenter, D. (2015). Key performance indicators: Developing, implementing, and using winning KPIs (3rd ed.). Wiley.

Case Study – Banking Sector KPIs…

Key KPIs in Banking

1. Loan Default Rate (Non-Performing Loans – NPL)
   - Percentage of loans not being repaid
   - Indicates credit risk and portfolio quality
2. Return on Assets (ROA)
   - Measures profitability relative to total assets
   - Indicates how efficiently assets generate earnings
3. Return on Equity (ROE)
   - Measures profitability relative to shareholder equity
   - Reflects financial performance and investor value
4. Fraud Detection Rate
   - Number or percentage of detected fraudulent transactions
   - Indicates effectiveness of risk management systems
5. Customer Retention Rate
   - Percentage of customers retained over time
   - Reflects customer satisfaction and loyalty

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Challenges in Business Analytics

- While business analytics provides significant value, organizations face multiple technical, organizational, and ethical challenges that can limit its effectiveness.
- Understanding these challenges is essential for successful implementation and sustainability.

Key Challenges

1. Data Quality Issues
- Incomplete, inconsistent, or inaccurate data
- Leads to misleading insights and poor decisions

2. Data Integration & Silos
- Data stored across multiple systems (ERP, CRM, databases)
- Difficulty in creating a unified view of the organization

3. Lack of Skilled Personnel
- Shortage of data analysts, data scientists, and domain experts
- Limits the ability to develop and interpret analytical models

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Challenges in Business Analytics…

Key Challenges

4. Technology & Infrastructure Constraints

- High cost of tools, storage, and computing resources
- Challenges in handling big data and real-time analytics

5. Data Privacy & Security

- Risks related to data breaches and misuse
- Need to comply with regulations and ethical standards

6. Organizational Resistance

- Resistance to change from traditional decision-making
- Lack of a data-driven culture

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Ethical Issues in Business Analytics

- Business analytics raises important ethical, legal, and social concerns due to the extensive use of personal and organizational data.
- Ethical analytics ensures that data is used in a way that is fair, transparent, and respects privacy rights.

Key Ethical Issues

1. Data Privacy

- Collection and use of personal data without proper consent
- Risk of misuse of sensitive customer information

Dignum, V. (2019). Responsible artificial intelligence: How to develop and use AI in a responsible way. Springer.

Ethical Issues in Business Analytics…

Key Ethical Issues

2. Data Security
- Vulnerability to data breaches and cyber attacks
- Unauthorized access to confidential business or customer data

3. Bias and Fairness
- Analytical models may reflect or amplify existing biases
- Leads to unfair decisions (e.g., credit scoring, hiring, pricing)

4. Transparency and Explainability
- "Black-box" models make decisions difficult to interpret
- Lack of transparency reduces trust in analytics systems

5. Accountability
- Unclear responsibility for decisions made by automated systems
- Need for governance structures in analytics deployment

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Future Trends in Business Analytics

- Business analytics is rapidly evolving due to advances in artificial intelligence, big data, cloud computing, and automation.
- Future analytics systems will be more autonomous, real-time, and decision-centric, enabling organizations to act faster and smarter.

Key Future Trends

1. Artificial Intelligence (AI) and Machine Learning Integration

- Deeper integration of AI in all analytics layers
- Automated pattern discovery and decision-making
- Reduced human intervention in routine analysis

2. Real-Time and Streaming Analytics

- Continuous processing of live data streams
- Immediate insights for operational decisions
- Example: fraud detection and live recommendation systems

Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. Harvard Business Review, 96(1), 108–116.

Future Trends in Business Analytics…

3. Augmented Analytics
- Use of AI to assist data preparation, insight generation, and visualization
- Enables non-technical users to perform advanced analytics

4. Explainable AI (XAI)
- Focus on transparency and interpretability of complex models
- Builds trust in AI-driven decisions

5. Edge Analytics and IoT Integration
- Processing data closer to the source (edge devices)
- Critical for smart cities, healthcare devices, and industrial IoT systems

6. Self-Service Analytics
- Business users independently explore data without IT dependency
- Increases agility and decision speed

Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review, 96*(1), 108–116.

Summary

- In todays lecture we have discussed about;
  - Key concepts of Business Analytics
  - Four types of analytics
  - Analytics concepts of real-world scenarios
  - Key Performance Indicators (KPIs)
  - Analytics decision-making process

References

- Provost, F., & Fawcett, T. (2013). Data science for business: What you need to know about data mining and data-analytic thinking. O'Reilly Media.
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