ABHYASMITRA.IN

STUDY NOTES

BUSINESS ANALYTICS

Unit IV – Business Analytics in Marketing and Finance

4.1 Marketing Analytics – Introduction

> **Definition**
> *"Marketing analytics is the practice of measuring, managing, and analysing marketing performance data in order to maximise effectiveness and optimise return on investment (ROI)."*

Marketing generates enormous amounts of data – from website visits, email campaigns, social media interactions, sales transactions, and customer surveys. Marketing analytics transforms this raw data into insights that help marketers understand what is working, what is not, and where to invest their marketing budget.

Why Marketing Analytics Matters

- **Proves Marketing ROI:** Shows exactly which campaigns and channels generated revenue, justifying marketing budgets.
- **Improves Targeting:** Identifies the most valuable customer segments and how to reach them effectively.
- **Optimises Campaigns:** Real-time data allows marketers to adjust campaigns in progress for better results.
- **Reduces Waste:** Identifies spending on channels or audiences that are not generating returns.
- **Enhances Customer Experience:** Personalises interactions based on customer behaviour and preferences.
- **Predicts Future Performance:** Forecasts the likely outcome of campaigns before they are launched.

Key Areas of Marketing Analytics

- Customer Analytics – understanding customer behaviour, preferences, and lifetime value.
- Campaign Analytics – measuring the effectiveness of marketing campaigns.
- Digital Analytics – analysing website, social media, and email performance.
- Product Analytics – understanding how customers use products and features.
- Pricing Analytics – optimising pricing strategies based on demand and competitor data.

4.2 Customer Segmentation, Targeting, and Positioning

The foundation of effective marketing is reaching the right customer with the right message at the right time. This is achieved through the STP framework: Segmentation, Targeting, and Positioning.

Customer Segmentation

> **Definition**
> *"Customer segmentation is the process of dividing a customer base into distinct groups of individuals that share similar characteristics, behaviours, or needs."*

Segmentation helps businesses avoid a one-size-fits-all approach and instead tailor their products, messaging, and service to specific customer groups.

- **Demographic Segmentation:** Dividing customers by age, gender, income, education, occupation. Example: Separate campaigns for millennials and baby boomers.
- **Geographic Segmentation:** Dividing by location – country, region, city, climate. Example: Promoting winter clothing only in cold regions.
- **Psychographic Segmentation:** Dividing by lifestyle, values, personality, and attitudes. Example: Targeting eco-conscious consumers with sustainable products.
- **Behavioural Segmentation:** Dividing by purchase behaviour, usage rate, brand loyalty, and buying stage. Example: Loyal customers vs first-time buyers vs churned customers.
- **RFM Segmentation (Recency, Frequency, Monetary):** A data-driven method that segments customers based on:
- Recency (R): How recently did they make a purchase?
- Frequency (F): How often do they purchase?
- Monetary (M): How much do they spend in total?

Analytics Tools for Segmentation: K-Means clustering, RFM analysis, decision trees, logistic regression.

Targeting

After segmentation, targeting is the process of evaluating each segment and selecting the most attractive ones to focus marketing efforts on. Criteria for evaluating a segment:

- **Size:** Is the segment large enough to be profitable?
- **Growth:** Is the segment growing or shrinking?
- **Profitability:** Can we make money from this segment?
- **Accessibility:** Can we reach this segment through our marketing channels?
- **Competition:** How many competitors are already targeting this segment?

Positioning

Positioning is the process of creating a distinct image and value proposition in the minds of the target customers. It answers: "Why should this customer choose us over the competition?"

- **Value Proposition:** The unique benefit the product provides to the target customer. Example: "The most affordable laptop for students" or "The most secure messaging app for businesses."
- **Perceptual Maps:** A visual analytical tool that plots products or brands on a two-dimensional graph based on customer perceptions. Helps identify gaps in the market and optimal positioning.

4.3 Campaign Management and ROI Measurement

Campaign Management

A marketing campaign is a coordinated set of marketing activities designed to achieve a specific goal (e.g., increase brand awareness, drive website traffic, generate leads, or boost sales) within a defined time period.

Analytics-driven campaign management involves:

- **Goal Setting:** Define SMART goals (Specific, Measurable, Achievable, Relevant, Time-bound). Example: Increase website conversions by 25% in Q4 2024.
- **Audience Selection:** Use customer segmentation data to target the right audience.
- **Channel Selection:** Choose the most effective channels (email, social media, search ads, display ads) based on where the target audience spends time.
- **A/B Testing:** Test two versions of a campaign element (subject line, image, call-to-action) to see which performs better.
- **Real-Time Monitoring:** Track campaign performance metrics daily or hourly and make adjustments.
- **Post-Campaign Analysis:** After the campaign, analyse overall performance, calculate ROI, and document learnings for future campaigns.

ROI (Return on Investment) Measurement

Formula
Marketing ROI = [(Revenue Generated by Campaign – Campaign Cost) ÷ Campaign Cost] × 100%

Example: Campaign Cost = ₹1,00,000. Revenue attributed to campaign = ₹3,50,000. ROI = [(3,50,000 – 1,00,000) ÷ 1,00,000] × 100% = 250%

Key Marketing Performance Metrics

Metric	Description	Example
Click-Through Rate (CTR)	Clicks ÷ Impressions × 100%	Email CTR of 3.5%
Conversion Rate	Conversions ÷ Total Visitors × 100%	2% of website visitors make a purchase
Cost Per Acquisition (CPA)	Total Campaign Cost ÷ Number of Acquisitions	Cost ₹500 to acquire one new customer
Customer Lifetime Value (CLV)	Total revenue expected from a customer over their lifetime	CLV of ₹10,000 per customer
Return on Ad Spend (ROAS)	Revenue ÷ Ad Spend	ROAS of 4 means ₹4 earned per ₹1 spent
Net Promoter Score (NPS)	Measures customer loyalty and likelihood to recommend	NPS of 70 is excellent

Customer Acquisition Cost (CAC)	Total Marketing Spend ÷ New Customers Acquired	CAC of ₹2,000 per new customer

4.4 Data-Driven Marketing Strategies

Data-driven marketing is an approach where marketing decisions are made based on data and analytics rather than intuition or assumptions. Data-driven marketers use customer insights to create highly personalised, timely, and relevant marketing experiences.

Key Data-Driven Marketing Strategies

- **Personalisation:** Using customer data to deliver personalised content, product recommendations, and offers. Example: Netflix recommending movies based on viewing history; Amazon recommending products based on purchase history. Personalisation increases engagement by 80% on average.
- **Predictive Lead Scoring:** Using machine learning to score leads (potential customers) based on their likelihood to convert into paying customers. Sales teams focus their effort on high-score leads first. Example: A B2B software company scores leads based on company size, industry, and engagement behaviour.
- **Churn Prediction and Retention Marketing:** Using predictive models to identify customers who are likely to stop using the product. Proactively reach out with targeted retention offers before they leave. Example: A telecom company identifies customers showing signs of churn (reduced call minutes, customer service complaints) and offers a discount.
- **Content Marketing Optimisation:** Analysing which types of content (blog posts, videos, infographics) drive the most engagement, leads, and conversions. Using these insights to prioritise content creation efforts.
- **Dynamic Pricing:** Adjusting prices in real-time based on demand, competitor prices, customer segments, and inventory levels. Example: Airlines and hotel booking sites use dynamic pricing extensively.
- **Omni-Channel Analytics:** Tracking customer interactions across all channels (website, mobile app, social media, in-store) to create a unified view of the customer journey. Example: A customer views a product on a mobile app, adds it to the cart on a desktop, and buys it in-store – all tracked as a single journey.

4.5 Financial Analytics – Introduction

Definition
"Financial analytics is the use of data analysis, statistical methods, and technology to extract insights from financial data that help organisations make better financial decisions, manage risk, and improve financial performance."

Financial analytics encompasses a wide range of applications – from basic financial reporting and budgeting to sophisticated risk modelling and fraud detection. It applies business analytics techniques specifically to financial data to improve financial planning, control, and decision-making.

Key Areas of Financial Analytics

- **Financial Performance Analysis:** Analysing financial statements (income statement, balance sheet, cash flow statement) to assess business health.
- **Budgeting and Forecasting:** Using historical financial data to create accurate budgets and financial forecasts.
- **Risk Management:** Identifying, measuring, and mitigating financial risks.
- **Investment Analysis:** Evaluating investment opportunities using analytical models.
- **Credit Analysis:** Assessing the creditworthiness of borrowers or business partners.
- **Fraud Detection:** Using analytics to detect unusual financial transactions that may indicate fraud.

4.6 Risk Management and Credit Scoring

Risk Management in Finance

Financial risk management is the process of identifying, measuring, and mitigating financial risks that could adversely affect an organisation's financial performance or stability.

- **Market Risk:** The risk of losses due to changes in market conditions (stock prices, interest rates, exchange rates). Analytics tools: Value at Risk (VaR), stress testing, scenario analysis.
- **Credit Risk:** The risk that a borrower will default on their debt obligations. Analytics tools: Credit scoring models, probability of default (PD) models, loss given default (LGD).
- **Operational Risk:** The risk of losses from inadequate internal processes, systems, or human errors. Analytics tools: Process mining, anomaly detection.
- **Liquidity Risk:** The risk that an organisation cannot meet its short-term financial obligations. Analytics tools: Cash flow forecasting, liquidity ratio analysis.

Value at Risk (VaR)

VaR is a widely used risk measure that quantifies the maximum potential loss of a portfolio over a specified time period at a given confidence level.

Example: "The 1-day VaR of a portfolio is ₹50 lakh at a 95% confidence level." This means there is a 95% probability that the portfolio will not lose more than ₹50 lakh in a single day.

Credit Scoring

Definition

> *"Credit scoring is a statistical analysis performed by financial institutions (banks, NBFCs) to determine the creditworthiness of an individual or organisation by assigning a numerical score based on their financial history and behaviour."*

Credit scoring determines whether a loan applicant is likely to repay their loan. A higher score indicates lower risk and makes it easier to get a loan at a lower interest rate.

Credit Scoring Methods

- **CIBIL Score (India):** India's most widely used credit score, ranging from 300 to 900. A score above 750 is generally considered excellent. Calculated by TransUnion CIBIL based on payment history, credit utilisation, credit age, and types of credit.
- **FICO Score (USA):** The standard credit scoring model in the United States, ranging from 300 to 850.
- **Machine Learning-Based Scoring:** Modern lenders use ML models (Logistic Regression, Random Forest, Gradient Boosting) to score credit applications based on hundreds of variables beyond traditional credit history.

Factors Used in Credit Scoring

Factor	Weightage (Approx.)	Description
Payment History	35%	Have you paid past credit accounts on time?
Credit Utilisation	30%	How much of your available credit are you using?
Length of Credit History	15%	How long have your credit accounts been open?
Credit Mix	10%	Do you have a variety of credit types (loan, credit card, mortgage)?
New Credit	10%	How many new credit applications have you made recently?

4.7 Financial Forecasting and Planning

Financial forecasting is the process of estimating future financial outcomes based on historical data, current trends, and assumptions about future conditions. Financial planning uses these forecasts to allocate resources, set targets, and make strategic decisions.

Types of Financial Forecasts

- **Revenue/Sales Forecast:** Predicts future sales revenue based on historical sales data, market trends, and business plans.
- **Expense Forecast:** Estimates future costs including fixed costs (rent, salaries) and variable costs (materials, commissions).

- **Cash Flow Forecast:** Predicts future cash inflows and outflows to ensure the business has sufficient liquidity.
- **Profit and Loss (P&L) Forecast:** Estimated future income statement showing projected revenues, expenses, and profit.
- **Balance Sheet Forecast:** Projected future financial position of the organisation.

Financial Forecasting Techniques

- **Straight-Line Method:** Assumes constant growth rate from historical data. Simple but not accurate for volatile data.
- **Moving Average:** Uses the average of recent periods to forecast the next period. Reduces the impact of short-term fluctuations.
- **Linear Regression:** Builds a statistical relationship between a financial variable (revenue) and one or more predictors (GDP, advertising spend).
- **Time-Series Analysis (ARIMA):** Models the patterns (trend, seasonality, cycles) in historical financial data to make future predictions.
- **Driver-Based Forecasting:** Identifies the key business drivers (number of customers, average transaction value, churn rate) and forecasts each driver separately, then combines them to produce the financial forecast.

Financial Planning Process

- **Step 1 – Define Financial Goals:** What profitability, growth, or liquidity targets does the business want to achieve?
- **Step 2 – Analyse Current Financial Position:** Review current financial statements, ratios, and trends.
- **Step 3 – Develop Forecast Scenarios:** Create base case, optimistic, and pessimistic scenarios.
- **Step 4 – Create the Financial Plan:** Develop budgets and resource allocation plans based on the chosen scenario.
- **Step 5 – Monitor and Revise:** Compare actual financial results against the plan and update forecasts regularly (rolling forecast).

4.8 Case Studies: Financial Performance Improvement Through Analytics

Analytics has been used by organisations worldwide to significantly improve their financial performance. The following case studies illustrate real-world applications of business analytics in finance. (Note: These are conceptual case studies – no statistical calculations are required.)

Case Study 1: Retail Bank – Reducing Loan Defaults

Background: A large retail bank was experiencing increasing loan default rates, leading to significant financial losses. The traditional credit scoring model was not identifying high-risk borrowers accurately.

Analytics Solution: The bank deployed a machine learning-based credit scoring model using a wider set of variables including digital transaction behaviour, utility payment history, and social media data (with consent). The model was significantly more accurate at predicting defaults than the traditional model.

Results:

- 25% reduction in loan default rates within 12 months.
- More loans approved for creditworthy customers who were previously rejected by the conservative traditional model.
- Estimated savings of ₹200 crore in bad debt provisions.

Key Analytics Used: Logistic Regression, Random Forest, Gradient Boosting, feature engineering.

Case Study 2: E-Commerce Company – Increasing Customer Lifetime Value

Background: A major e-commerce platform noticed that while it was acquiring many new customers, a large proportion were making only one purchase and never returning. This high churn rate was damaging profitability because customer acquisition costs were high.

Analytics Solution: The company built a Customer Lifetime Value (CLV) prediction model and a churn prediction model. High-CLV customers were identified for premium service and personalised offers. Customers identified as "at risk of churning" were targeted with personalised re-engagement campaigns and loyalty rewards.

Results:

- 35% increase in repeat purchase rate among targeted customers.
- 20% increase in average CLV across the customer base.
- 15% reduction in customer acquisition costs due to improved retention.

Key Analytics Used: RFM Analysis, K-Means Clustering, Logistic Regression for churn prediction, A/B testing for campaign effectiveness.

Case Study 3: Manufacturing Company – Supply Chain Cost Reduction

Background: A large manufacturing company had high and unpredictable supply chain costs. Inventory levels were often either too high (leading to storage costs) or too low (leading to production stoppages).

Analytics Solution: The company implemented a demand forecasting system using time-series analysis and machine learning. The model incorporated historical sales data, seasonal patterns, promotional calendars, and external economic indicators to produce accurate demand forecasts. Inventory levels were optimised based on these forecasts.

Results:

- 30% reduction in inventory holding costs.
- Production stoppages due to material shortages reduced by 80%.

- Overall supply chain cost reduced by 18%.

Key Analytics Used: ARIMA time-series forecasting, linear optimisation for inventory planning, simulation.

Case Study 4: Insurance Company – Fraud Detection

Background: An insurance company was losing significant revenue to fraudulent claims. Manual review of claims was slow, expensive, and only detected a small fraction of fraudulent activity.

Analytics Solution: The company built a real-time fraud detection system using anomaly detection and classification algorithms. The model analysed hundreds of variables per claim including claim patterns, claimant history, and social network analysis (identifying organised fraud rings).

Results:

- Fraudulent claims detection rate increased from 20% to 78%.
- Estimated ₹150 crore saved annually in fraudulent claim payouts.
- Claims processing time for legitimate claims reduced by 40% as fewer claims required intensive manual review.

Key Analytics Used: Anomaly detection, Random Forest classification, social network analysis, real-time streaming analytics.

Summary: Financial Analytics Value Chain

Application Area	Analytics Used	Business Outcome
Credit Scoring	ML Classification	Reduced loan defaults
Fraud Detection	Anomaly Detection, Classification	Reduced fraud losses
Revenue Forecasting	Time-Series, Regression	Better financial planning
Customer CLV	RFM Analysis, Clustering	Improved retention and revenue
Risk Management	VaR, Stress Testing	Better risk-adjusted returns
Supply Chain	Forecasting, Optimisation	Lower costs, fewer stockouts
Investment Analysis	Portfolio Optimisation	Higher returns per unit of risk