

An abstract graphic on the left side of the slide. It features a central glowing yellow sphere with radiating lines, surrounded by a complex network of white and orange circuit-like lines on a light beige background. The lines form a funnel-like shape that narrows towards the sphere.

# Strategic Data Analysis for Decision Making

Transforming Data into Insights and Insights into Action

**Presenter:** Yan Aditiya Pratama

**Institution:** Institut Informatika dan Bisnis Darmajaya

**Year:** 2025

# Presentation Roadmap

01

---

## Introduction

From Gut Feeling to Data-Driven Decisions

03

---

## Part 2

The Art and Science of Interpreting Analysis Results

05

---

## Part 4

Case Study: Real-World Application

02

---

## Part 1

Data Analysis Techniques: Descriptive, Diagnostic, Predictive, Prescriptive

04

---

## Part 3

Building a Data-Driven Decision-Making Culture

06

---

## Conclusion

Key Takeaways and Initial Steps

A 3D rendering of a staircase with four steps, symbolizing progression and levels. The steps are light beige and set against a warm, orange-toned background with soft shadows.

# The Four Levels of Data Insights

Modern data analysis frameworks divide analytics into four progressive levels, each building deeper understanding for strategic decisions.

# Descriptive Analytics: What Happened?

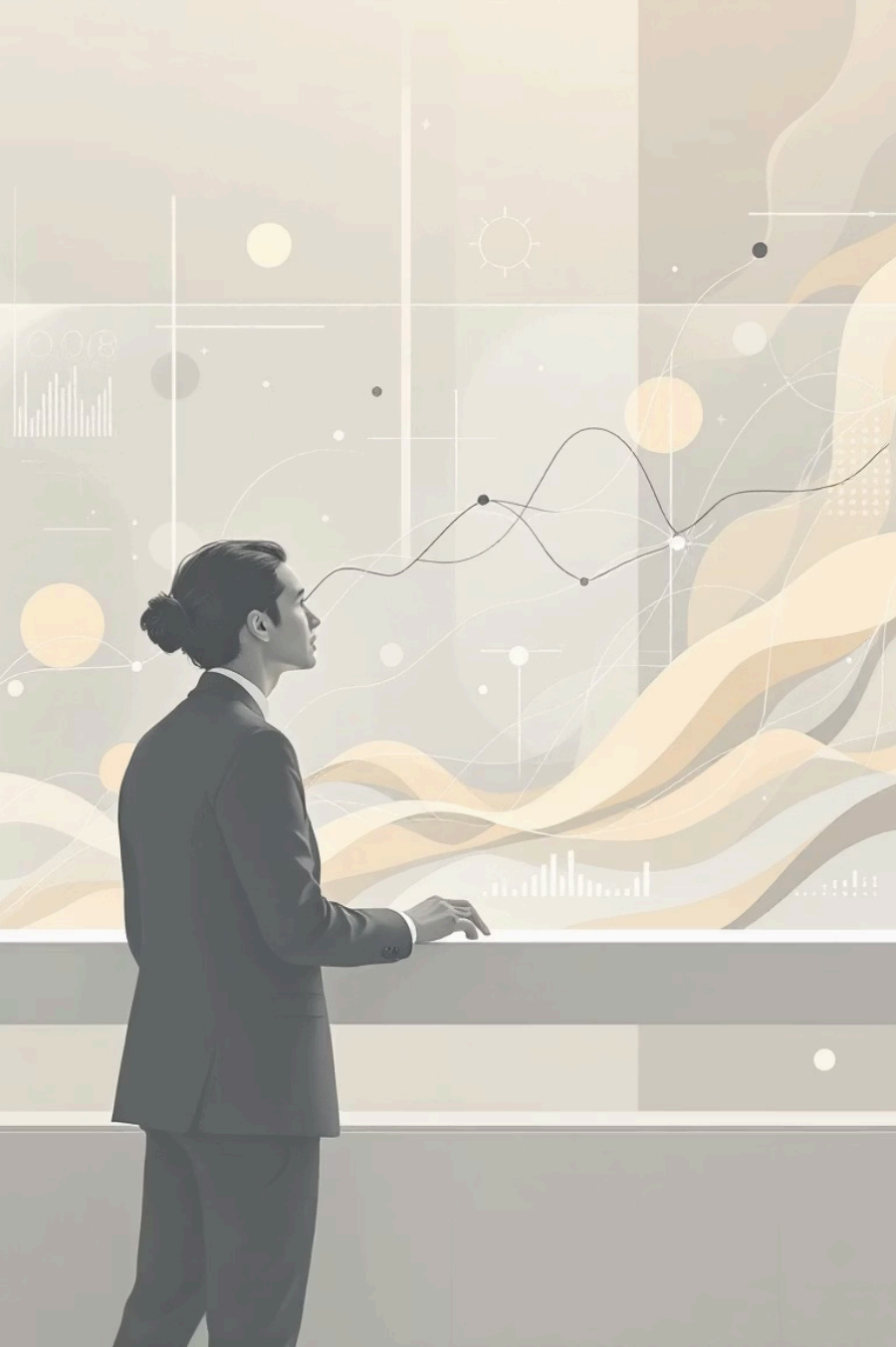
Focuses on historical data to understand past performance.

**Techniques:** Dashboards, summary reports (sums, averages, counts), visualizations like graphs and charts.

**Example:** "Q3 sales dropped 15% compared to Q2, revealing seasonal trends."

## Key Benefits

Provides baseline metrics for tracking business health and identifying immediate issues.



# Diagnostic and Predictive Analytics

## Diagnostic: Why Did It Happen?

Investigates root causes behind events.

**Techniques:** Drill-down analysis, correlations, root cause investigations.

**Example:** "Sales decline correlates with reduced website traffic post-SEO algorithm update."

## Predictive: What Will Happen?

Forecasts future outcomes using historical patterns.

**Techniques:** Regression models, machine learning, forecasting tools.

**Example:** "Seasonal data predicts 20% demand surge in December from marketing efforts."

# Prescriptive Analytics: What Should We Do?

Recommends optimal actions based on predictions to maximize outcomes.

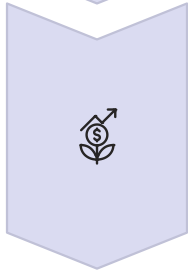
**Techniques:** Optimization algorithms, simulations, A/B testing.

**Example:** "Increase stock at Warehouse Y and launch promotions in Region Z to boost profits by 25%."



## Actionable Recommendations

Guides resource allocation for competitive advantage.



## Strategic Optimization

Simulates scenarios to test decision impacts before implementation.



# Interpreting Results: Beyond the Numbers

Effective interpretation turns raw data into reliable business intelligence. Key principles ensure accuracy and relevance.

## Context is Key

A 10% decline means little without benchmarks—compare to industry norms or competitors for true perspective.

## Correlation vs. Causation

Ice cream sales correlate with drownings, but summer heat causes both. Beware spurious correlations in decision-making.

## Statistical and Practical Significance

Findings may be statistically valid but lack business impact—prioritize what drives real value.

## Right Visualization for the Story

Use line charts for trends, bars for comparisons, pies for proportions to communicate clearly and avoid misleading audiences.



# Data-Driven Decision Making (DDDM)

Definition: A systematic process where decisions stem from data analysis rather than intuition alone, fostering objectivity in business leadership.

**Why It Matters:** Reduces biases like confirmation bias, enhances accuracy for accountable choices, and optimizes resources for maximum impact.



# Case Study: Boosting EduLearn App Engagement

Background: The "EduLearn" learning app faced declining course completion rates, prompting a data-driven turnaround.

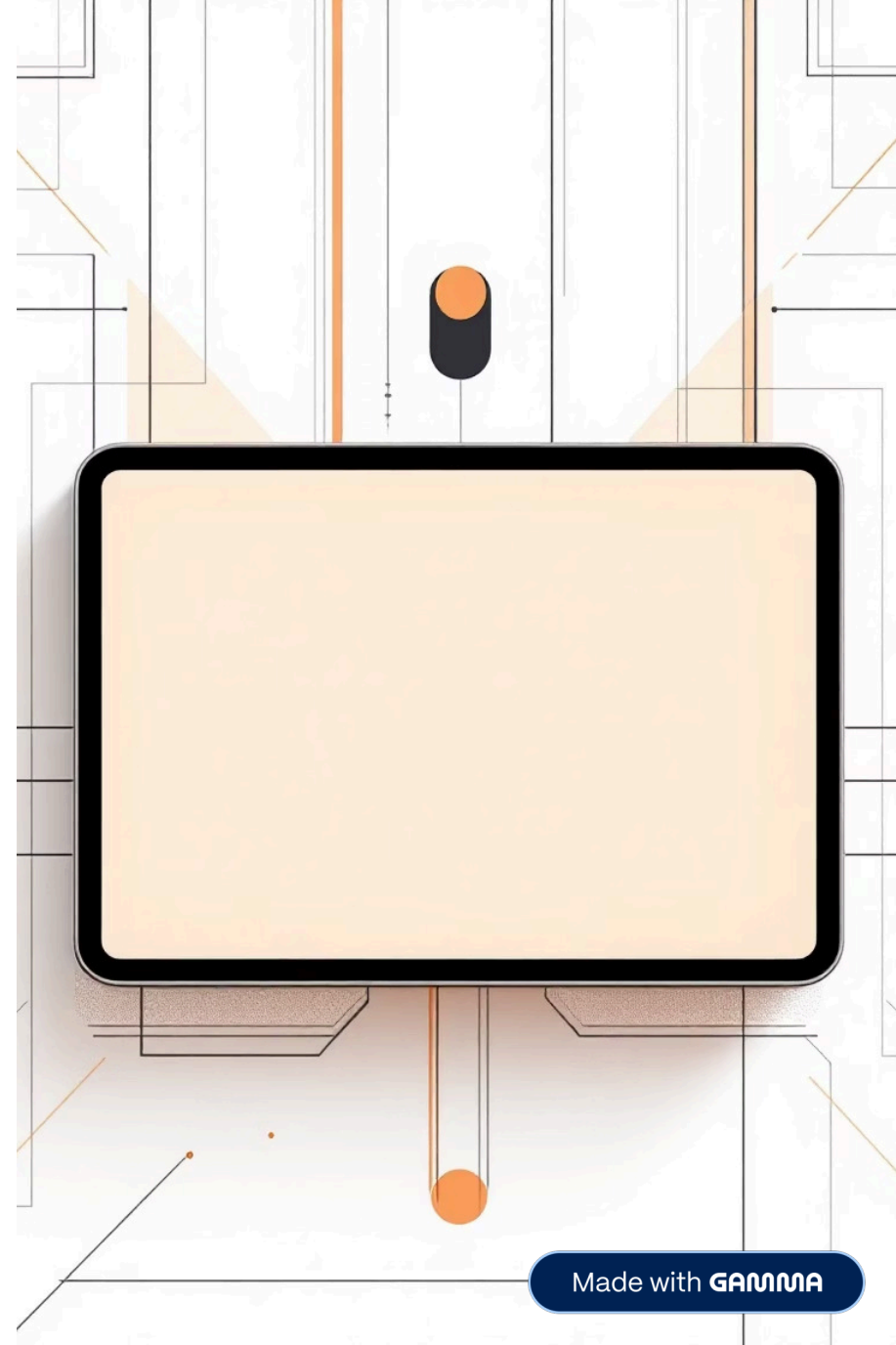
## Descriptive & Diagnostic Steps


Dashboard revealed 60% dropout in "Basic Programming" Module 3. User behavior analysis linked it to a confusing OOP video, confirmed by surveys noting its fast pace and complexity.

Implementation: A/B tested revisions; new version lifted Module 3 completion by 35% in one month, validating the approach.

## Predictive & Prescriptive Actions

Forecasts warned of ongoing reputational damage. Recommendations: Split video into three simpler segments with interactive quizzes.





# Case Study Analysis: EduLearn App Engagement

The EduLearn case study exemplifies a systematic application of Data-Driven Decision Making (DDDM) through all analytical stages.

01

---

## **Descriptive: What Happened?**

Dashboard tracking revealed a 60% dropout rate in "Basic Programming" Module 3, quantifying the problem.

02

---

## **Diagnostic: Why It Happened?**

User behavior analysis and surveys linked dropouts to a confusing "OOP Concepts" video (too fast/complex).

03

---

## **Predictive: What Will Happen?**

Forecasts indicated ongoing reputational damage and revenue decline if the issue remained unaddressed.

04

---

## **Prescriptive: What Should We Do?**

Recommended splitting the video into three simpler segments with interactive quizzes to reduce cognitive load.

05

---

## **Implementation & Evaluation**

A/B testing showed the new module boosted completion by 35% in one month, validating the data-driven solution.

06

---

## **Key Conclusions**

This process highlights data-driven problem identification, root cause analysis, impact assessment, and validated solution design.

# Conclusion: Integrate Data, Ethics, and Emotion

Data analysis empowers strategic decisions but must blend with leadership wisdom, ethical considerations, and emotional intelligence for humane, responsible outcomes.

## Start with Business Questions

Frame inquiries first; let data answer them effectively.

## Initial Steps for DDDM

1. Identify one data-solvable problem.
2. Use existing data sources.
3. Foster "why" questioning.
4. Run small A/B experiments.

## References:

Evans, J. R. (2013). *\*Business Analytics\**. Pearson.

Provost, F., & Fawcett, T. (2013). *\*Data Science for Business\**. O'Reilly.

Wheelan, C. (2013). *\*Naked Statistics\**. W. W. Norton.

Davenport, T. H., & Harris, J. G. (2007). *\*Competing on Analytics\**. Harvard Business Review Press.